MASTER OF SCIENCE IN FINANCE

MASTERS FINAL WORK

PROJECT

PERFORMANCE OF TARGET PRICES

JOANA RAQUEL NEVES ALMEIDA

OCTOBER 2019

LISBON SCHOOL OF ECONOMICS & MANAGEMENT
UNIVERSIDADE DE LISBOA

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Abstract

Equity researches are conducted by professionals who advise investors about stocks. Target prices consider not only market demand and supply factors, but also the opinions of each analyst.

In this study, we analyze the performance of target prices, using two different approaches. First, we study the predictive power of 12-month price targets comparing it to a simple capitalization rule based upon past returns. Second, we analyze the performance of an active portfolio based upon analysts' price targets and compare it to the naïve homogeneous portfolio, as well as to a market index and the mean-variance tangent portfolio.

We find price targets have no predictive power on future 12-month market prices. In that respect, we show the simple capitalization rules do equally (bad).

In terms of portfolio performance, we find the active managed portfolio based upon analysts' recommendations does not outperform the other portfolios. Our results are robust to alternative rebalancing schemes.

Our analysis is based upon 50 European stocks over a 15-year period, from 2004 to 2019.

JEL Codes: B16, C12, C32, C33, C61, G11, G17, L10, L25.

Keywords: Target Prices, Non-stationary and stationary variables, Homogeneous, Active and Tangent portfolios, Optimal portfolio, Return, Risk, Sharpe-ratio.

Resumo

As avaliações de ações são conduzidas por profissionais que aconselham os investidores sobre ações. Os *Target prices* consideram não apenas os fatores de procura e oferta de mercado, mas também as opiniões de cada analista.

Neste estudo, analisamos o desempenho dos *Target prices*, usando duas abordagens diferentes. Primeiro, estudamos o poder preditivo dos *Target prices* a 12 meses comparando-as a uma regra de capitalização simples com base nos retornos passados. Segundo, analisamos o desempenho de uma carteira activa construída tendo por base os *price-targets* e comparamos com a carteira homogénea, bem como o índice de mercado e a carteira tangente de variância média.

Concluímos que os *price-targets* não têm poder preditivo nos preços futuros do mercado a 12 meses. A esse respeito, mostramos que as regras simples de capitalização são igualmente (más).

Em termos de desempenho da carteira, descobrimos que a carteira activa construíra com base nas recomendações dos analistas não supera os outros portfólios. Os nossos resultados são robustos a esquemas alternativos de rebalanceamento de carteiras.

A nossa análise é baseada em 50 ações europeias durante um período de 15 anos, de 2004 a 2019.

JEL Codes: B16, C12, C32, C33, C61, G11, G17, L10, L25.

Palavras Chave: *Target prices*, Variáveis estacionárias e não estacionárias, Carteiras homogénea, activa e tangente, Carteira óptima, Retorno, Risco, Índice Sharpe.

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1. Introduction

Currently, millions of shares are traded daily on world markets. Investors who buy and sell a share wonder if they are trading at the right price and if that value is its fair value.

Investors may face this problem in different ways. Intuitive investors rely on their own instinct, passive investors believe in market efficiency - they consider the market price to be the fair price to risk, on the contrary, active investors consider that it is possible to outperform the market return. Professional analysts, who specialize in this area, may also help investors decide, given recommendations and, or computing target prices.

Typically, a short-term target price is more reliable than a long-term one but, on average, 12-month target prices are a market replace.

Most equity research and price targets are carried out by high status entities such as consulting firms and investment banks. It turns out that the reputation of these entities ultimately influences significantly the behavior of investors. In doing so, analysts' work consists of predicting profits, forecasting long-term stock price trends and anticipating future stock prices.

Nowadays, price targets of financial analysts are available to investors via platforms such as Bloomberg. Although price target may vary from analyst to analyst – depending on the models they use and parameter estimations, investors can also use them to decide their investment strategy.

Most studies have focused on the effect of analyst recommendations on stock returns. However, the study of target price efficiency in forecasting future stock prices remains under-explored.

In this study, we investigate analysts' recommendations over the past 15 years on 50 of the largest European stocks. We analyze both the predictive power of price targets, comparing it to sample capitalization of current prices, and evaluate the performance of an active portfolio built based upon analysts' recommendations.

This research is relevant to both finance scholars and investment professionals. From an investor's perspective, it helps in understanding how analysts' forecasts and recommendations can be used (and how reliable they are) for investment purposes. For the literature, this study takes a different perspective than what is standard by analyzing both the predictive power of price targets and its practical use in the context of active portfolios.

The research questions of this work are:

- Can the price targets predict future prices better than capitalized values of the current stock price?
- Given analysts' recommendation, can an active portfolio based upon the spread between the price target and current price, beat the market, the mean-variance tangent portfolio, or even the naïve homogeneous portfolio?

Our empirical results are based on a sample of 783 observations collect (for each of the 50 companies) and target prices collected from Bloomberg during 2004 to 2019.

The rest of the text is organized as follows. Section 2 presents the literature review. Section 3 describes the data collection process. Section 4 is divided in two. Sub-section 4.1. describes the methods used to forecasting power of 12-month target prices. Sub-section 4.2. explains the methodology used for portfolio performance analysis. Section 5 shows and discussed the results. Finally, in Section 6 we summarize the main results, present the limitations and suggestions for future research.

2. Literature Review

Graham and Dodd (1951) defined the role of analysts is to determine some objective value (target price), independent of the market quotation.

Valuation is the process used to determine the current or projected value of an asset or a company. Depending on the beliefs, models, and points of view of analysts, it is possible to evaluate a company and conclude about the “fair” value of a stock.

A price target is nothing but the projected future “fair” price an asset at a pre-defined future date, as stated by an investment analyst. It is based on assumptions about the asset's future supply and demand, technical assumptions, and fundamentals. A recommendation is determined by comparing the current market price of the stock against a price target (Stickel, 2016). A strong buy or buy recommendation indicates that the stock is underpriced (price target exceeds the current market price), a hold recommendation indicates the current market price is about fair and a strong sell or sell indicates the stock is overpriced (the price target is less than the current market price).

Bonini, Zanetti and Bianchini (2005) showed that the forecast errors are high and are positively correlated with the research intensity. In addition, they found that research intensity is related to increased forecasting errors as major companies provide less information. Finally, they concluded that the results of the research activities are poorly informative.

To support the previous study, Bonini, Zanetti, Bianchini and Salvi (2010) report two main reasons for the target prices to differ across analysts and from the current market price. The first reason is that the information that is available to analysts may differ from what is available in the market. The second is that assumptions are made by analysts about the company's future cash flows on a different note. They also report exaggerated target prices, that result in an incentive to transfer the risk of trained and informed investors to the least informed.

Sorescu and Subrahmanyam (2006) reported that analysts' experience counts on the credibility of target price information, as more experienced analysts offer more information on the recommendations.

It is well-known, that the majority of analysts' recommendations are recommendations to buy. One of the reasons can be conflict of interests because analysts' that make recommendations are usually directly related to the company under analysis. Bradshaw, Huang and Tan (2012) suggest that investment bank pressures aggravate analysts' optimism about target prices. For this reason and due to the conflict of interest in the business some investment banks were objects of severe criticism. Nonetheless, there is evidence that, for the most part, analysts' recommendations provide useful information. Thus, some studies emphasize that the analysts' recommendations can discriminate more accurately the devalued shares of overvalued stocks. This happens if the conflict of interest is removed.

Lin and MicNichls (1998) showed that the growth forecasts of affiliated analysts are significantly more favorable than those of unfiled analysts. They also concluded that the results may reflect the issuers' incentives to select the investment bank where analysts give more favorable recommendations.

Jagadesh et al (2004) have concluded that it can be dangerous to follow analysts' recommendations. This study reinforced the idea that sometimes an analyst's assessment of the target price can be a reality bias.

On the other hand, Bradshaw and Brown (2006) claim that analyst compensation increases with accuracy of their forecasts and stock recommendations. Dechow, Hutton and Sloan (2000) find a positive relation between the fees paid to the affiliated analysts' employers and the currency of forecasts.

Furthermore, Asquith et al. (2005) studied the precision of a price target prediction concluding that to be accurate the 12-month projected price target needs to be equal to analyzed firm's stock at any time during the year following the release of a report. Take this definition into consideration, the result is that about 54% of "all American" analysts' price targets are achieved or exceeded.

Modern portfolio theory, developed by Markowitz (1952), states that investment selection decisions must be made based on the relationship between risk and expected return. While the benefits of diversification are clear, the determination of optimal, “tangent” portfolios depend on future expected returns. One way to overcome this problem is to use expected returns implicit in analysts price targets.

The existing literature on analyst recommendations has focused mainly on companies and has simply shown that analyst recommendations have informational power. Studies such as Womack (1996) report that updates (downgrades) in analyst recommendations are associated with abnormal positive (negative) returns after they are announced. Howe, Unlu and Yan (2009) later pointed out that future market and sector returns are predicted by changes in analysts' recommendations. This study showed that analysts' recommendations cover market and industry information.

Feldman, Livnat and Zhang (2012) studied the immediate and delayed market effects of analyst reviews of earnings forecasts, target prices and recommendations. This study proved that the three types of revisions are significantly related to market reactions. In addition, the authors report that investors can achieve high returns by combining the three revisions. In conclusion, portfolios based on target prices achieve superior returns.

Green (2006) showed that if there are transactions following the recommendations changes, the performance of the recommendations-based investment strategies increases significantly. Overall, the value of analyst research indicates that exclusivity is a relevant factor. This means that customer value can be increased if there are forces to delay the spread of analyst recommendations. Blau and Wode (2012) studied that short sellers are not informed of changes in recommendations. Which means that the short sale is considered to be speculative and not reported.

3. Data

We collected data on 50 major European companies that belonged to the EURO STOXX 50 during the last 15 years. We choose the ones that stayed the longest in the Index.

The EURO STOXX 50® Index is a major stock market index which tracks the performance of 50 Blue-chip companies based in twelve Euro Area countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain. The Index composition is revised on an annually basis in September. Its calculation occurs every 15 seconds between 09:00 CET and 18:00 CET for the EUR and USD variants of any return type, while the CAD, GBP and JPY variants are available as end-of-day calculation only (18:00 CET). Is calculated by weighting the companies that compose it through their financial capitalization. We can better understand with the Laspeyres formula:

$$Index_t = \frac{\sum_{i=1}^{n}(p_{it} \times s_{it} \times ff_{it} \times cf_{it} \times x_{it})}{D_t} = \frac{M_t}{D_t} \quad , \qquad (1)$$

where:

t = Time the index is computed;

n = Number of companies in the index;

p_{it} = Price of company (i) at time (t);

s_{it} = Number of shares of company (i) at time (t);

ff_{it} = Free float factor of company (i) at time (t);

cf_{it} = Weighting cap factor of company (i) at time (t);

x_{it} = Exchange rate from local currency into index currency for company (i) at time (t);

M_t = Free-float market capitalization of the index at time (t);

D_t = Divisor of the index at time (t).

Changes in weights due to corporate actions, such as (a cash dividend, a stock split, a reverse split, mergers and acquisitions, a spin-off and a company implementing a rights issue), are distributed proportionally across all index components. The index divisors, which is adjusted to maintain the continuity of the values of the index across changes due to corporate actions, are calculated as follows:

$$D_{t+1} = D_t \times \frac{\sum_{i=1}^{n}(p_{it} \times s_{it} \times ff_{it} \times cf_{it} \times x_{it}) \pm \Delta MC_{t+1}}{\sum_{i=1}^{n}(p_{it} \times s_{it} \times ff_{it} \times cf_{it} \times x_{it})} \quad , \tag{2}$$

where:

ΔMCt+1 = The difference between the closing market capitalization of the index and the adjusted closing market capitalization of the index, for companies with corporate actions effective at time (t+1);

The free-float market capitalization is calculated with adjusted closing prices, the new number of shares at time (t+1) and the free-float factor at time (t+1) minus the free-float market capitalization calculated with closing prices, number of shares at time (t) and free-float factor at time (t).

This formula shows that the companies with the largest capitalizations have a greater weight than those with lower capitalization.

Since our goal is to analyze the same 50 companies during our analysis period, we have decided to choose 50 companies that stayed longest in the index from 27/4/2004 to 23/4/2019.

Concretely we analyze the following companies:

a) 18 French (Air Liquide SA, Airbus SE, AXA SA, BNP Paribas SA, Carrefour, Danone SA, EssilorLuxottica SA, L'Oréal SA, LVMH Moet Hennesssy Louis Vuitton SE, Orange SA, Safran SA, Saint Gobain, Sanofi, Schneider Electric SE, Societe Generale SA, Total SA, Vinci SA, Vivendi SA);
b) 15 German (Adidas, Allianz SE, BASF SE, Bayer AG, Bayerische Motoren Werke AG (BMW), Daimler AG, Deutsche Bank, Deutsche Post AG, Deutsche Telekom AG, E.ON, Fresenius SE & Co KgaA, Munich Re, SAP SE, Siemens AG, Volkswagen AG);

c) 5 Italian (Assicurazioni Generali, Enel SpA, Eni SpA, Intesa Sanpaolo SpA, Unibail Rodamco Westfield, Unicredit);
d) 6 Spanish (Banco Bilbao Vizeaya Argentaria SA, Banco Santander SA, Iberdrola SA, Industria de Diseno Textil SA, Repsol, Telefonica SA);
e) 4 Dutch (ASML Holding NV, ING Groep NV, Koninklijke Philips NV, Unilever NV);
f) 1 Belgian (Anheuser-Busch Inbev SA/NV);
g) 1 Finnish (Nokia OYJ).

As we can see, we do not focus on any particular sector. In fact, the above list of companies include a variety of different sectors: Air Fright & Logistics; Airspace & Defense; Automobile manufactures; Chemicals; Construction & Engineering; Consumer durables & Apparel; Diversified chemicals; Diversified banks; Electric Components & Equipment; Electric Utilities; Food Products; Food, beverage & Tobacco; Health Care Equipments; Industrial Conglomerates; Integrated Oil & Gas; Integrated Telecommunication Services; Movies & Entertainment; Multi-line Insurance; Personal Products; Pharmaceuticals; Real State; Reinsurance; Retailing; Semiconductors, Software; Technology Hardware & Equipment; Hypermarkets, supermarkets, convenience stores, cash & carry, e-commerce.

We collected historical weekly values of the price targets from Bloomberg. As the data was collected on April 23 of 2019, Tuesday, the platform extract Tuesdays closed prices. Besides the data on individual stocks, we have also collected weekly values of EURO STOXX 50® total returns Index to take into account the dividends.

3.1. Variables

Our key variables are:

- FP: Actual close prices 12M ahead,
- TP: 12M Tgt Px[1],

[1] Where the closing prices are the current prices collected and 12M Tgt Px is considered the 12-month price target a consensus or average value (TP). So, for ticker Bloomberg calculate the price targets that are only for a 12-month time frame and that are less than 3-months old.

- CP: Current market prices simple 12M capitalized using past average returns.

The CP is calculated by the following formula:

$$CP_t = Price_t \times e^{\bar{R}\times 52} \quad , \qquad (3)$$

where $\bar{R}$ is the weekly average past return.

3.2. Descriptive statistics

In Table 1 we present the descriptive statistics of aggregate returns on our variables for each of the 50 stocks under analysis which are closer to normality but still not normal. We see that the aggregate returns are not normally distributed (skewness values are different from zero and kurtosis values differ from three for all variables).

Table 1 - Returns descriptive statistics (annualized values)

	Mean	Median	Volatility	Kurtosis	Skewness	Minimum	Maximum	Largest(52)	Smallest(52)	Confidence (95%)
Adidas	20,06%	16,59%	27,49%	5,3290	-0,0899	-1178,98%	1363,11%	286,55%	-262,70%	13,91%
Air Liquide	11,84%	17,05%	19,86%	4,1989	0,3308	-616,43%	1066,07%	210,11%	-200,58%	10,05%
Airbus	18,44%	13,93%	32,71%	1,9283	0,2131	-820,37%	1092,53%	345,17%	-303,63%	16,56%
Allianz	14,22%	22,64%	30,73%	19,4243	0,4562	-1790,24%	2235,18%	275,42%	-256,76%	15,55%
Anheuser	16,80%	23,22%	26,21%	13,4839	-0,7983	-1781,48%	1180,48%	256,67%	-225,94%	13,27%
ASML	22,27%	24,21%	29,73%	0,6755	0,0597	-737,20%	951,85%	340,93%	-300,55%	15,05%
Assicurazioni	5,32%	8,42%	26,83%	2,9920	-0,0320	-977,90%	1013,69%	279,52%	-277,15%	13,58%
AXA	13,28%	21,58%	37,63%	9,7664	0,3143	-1624,05%	2144,91%	356,64%	-340,15%	19,05%
Banco Bilbao	5,90%	10,99%	34,10%	7,9027	0,5577	-1433,22%	1940,49%	308,22%	-338,39%	17,26%
Banco Santander	7,37%	10,82%	32,76%	6,3357	0,2850	-1446,62%	1606,94%	339,52%	-310,23%	16,58%
BASF	15,53%	24,00%	27,80%	18,1044	1,3086	-909,31%	2170,40%	263,29%	-269,29%	14,07%
Bayer	13,58%	21,20%	27,58%	2,4724	-0,2521	-942,27%	949,84%	282,75%	-271,68%	13,96%
BNP Paribas	10,20%	5,99%	36,55%	4,9108	-0,1116	-1573,68%	1198,83%	360,34%	-340,54%	18,50%
BMW	12,31%	14,05%	31,24%	7,0854	0,6875	-989,53%	1808,52%	322,88%	-288,05%	15,82%
Danone	9,25%	5,84%	19,43%	1,2439	0,2529	-522,39%	593,29%	213,74%	-185,00%	9,84%
Carrefour	1,15%	0,00%	26,06%	0,9325	-0,0552	-768,83%	617,33%	277,12%	-288,52%	13,19%
Daimler	12,08%	15,01%	34,57%	12,1469	0,7603	-1352,99%	2346,87%	349,18%	-318,90%	17,50%
Deutsche Bank	-2,32%	-0,87%	41,84%	19,4014	1,1208	-1896,02%	3207,08%	375,54%	-400,63%	21,18%
Deutsche Post	11,08%	18,61%	28,23%	21,9285	0,3915	-1754,82%	2108,11%	256,58%	-259,25%	14,29%
Deutsche Telekom	7,95%	0,00%	21,39%	2,3396	0,1209	-706,17%	759,12%	242,57%	-200,86%	10,83%
E.ON	5,17%	11,29%	28,52%	11,3966	0,6569	-1029,37%	1916,88%	279,80%	-269,65%	14,43%
ENEL	8,87%	19,57%	23,29%	2,4837	-0,1618	-817,14%	848,07%	250,60%	-256,00%	11,79%
ENI	8,09%	19,17%	24,01%	5,9714	0,4829	-634,01%	1375,36%	227,93%	-252,12%	12,15%
Essilor	13,22%	13,87%	20,23%	3,0784	0,1383	-519,86%	881,29%	215,37%	-187,13%	10,24%
Fresenius	17,07%	13,71%	25,37%	2,8480	-0,4883	-1132,31%	596,39%	278,30%	-240,86%	12,84%
Iberdrola	12,13%	18,04%	24,63%	5,7101	-0,0114	-887,43%	1257,76%	247,62%	-245,45%	12,47%
Inditex	19,11%	17,90%	25,75%	2,2609	-0,1380	-789,37%	837,40%	294,88%	-244,46%	13,04%
ING	12,02%	10,49%	45,93%	17,4781	0,7983	-2055,81%	3157,14%	380,12%	-364,58%	23,25%
Intesa Sanpaolo	10,97%	19,19%	39,32%	9,0593	0,5933	-1573,33%	2408,82%	372,83%	-379,91%	19,90%
Philips	9,25%	20,45%	27,44%	3,6709	0,0503	-850,83%	1355,51%	271,57%	-280,31%	13,89%
L'Oreal	12,60%	12,39%	19,86%	1,3817	-0,0568	-618,76%	504,83%	233,78%	-189,47%	10,05%
LVMH	17,62%	26,58%	25,49%	3,9495	-0,1820	-1198,73%	913,70%	265,56%	-250,22%	12,90%
Mucich RE	12,39%	19,09%	22,08%	6,3136	0,4822	-624,85%	1311,75%	221,58%	-223,36%	11,17%
Nokia	4,62%	9,24%	37,55%	5,0594	0,2952	-1014,63%	1704,20%	374,67%	-364,91%	19,01%
Orange	6,41%	3,95%	22,52%	1,6730	0,2466	-619,75%	865,46%	243,15%	-232,57%	11,40%
Repsol	8,38%	9,99%	29,43%	6,2370	0,0487	-1447,25%	1290,28%	289,18%	-281,97%	14,90%
Safran	19,12%	18,97%	29,69%	3,3158	-0,0179	-1201,59%	1158,70%	314,36%	-287,43%	15,03%
Saint-Gobain	7,80%	10,57%	32,54%	7,0626	0,6096	-1079,64%	1907,98%	336,25%	-322,50%	16,47%
Sanofi	8,26%	6,75%	20,99%	1,4015	-0,2523	-606,85%	640,54%	219,98%	-218,87%	10,63%
SAP	11,80%	12,44%	24,07%	12,0035	-0,3968	-1510,51%	1326,72%	246,95%	-228,17%	12,18%
Schneider Electric SE	13,70%	17,41%	28,38%	2,2584	0,1813	-749,33%	1147,32%	296,01%	-275,73%	14,37%
Siemens	10,70%	10,30%	29,32%	17,9712	0,6382	-1504,12%	2173,04%	284,50%	-258,39%	14,84%
Societe Generale	7,17%	-1,26%	43,90%	6,4264	0,5466	-1620,20%	2139,34%	402,09%	-408,50%	22,22%
Telefonica	4,56%	6,65%	22,75%	5,1712	0,2215	-963,93%	1110,84%	219,79%	-227,28%	11,51%
Total	9,24%	14,81%	21,99%	2,4248	0,0847	-566,61%	938,36%	230,69%	-227,74%	11,13%
Unicredit	0,37%	-7,25%	49,22%	8,9595	0,6187	-2178,26%	2314,12%	430,39%	-429,87%	24,91%
Unilever	11,90%	12,64%	18,52%	2,4905	0,0729	-675,32%	596,09%	201,96%	-185,71%	9,37%
Vinci	17,07%	19,21%	26,09%	5,5106	0,4951	-762,84%	1465,77%	285,37%	-247,62%	13,21%
Vivendi	9,27%	9,44%	22,59%	1,9004	-0,1431	-888,06%	603,20%	255,64%	-215,97%	11,44%
Volkswagen	21,59%	15,89%	37,40%	7,4497	-0,6334	-1942,45%	1148,43%	370,80%	-345,27%	18,93%

This is equivalent to analyzing weekly, monthly, semi-annual and annual returns of the naïve homogeneous portfolio. Because when we make the average return and volatility of each company, we obtain the same values as represented in Table 1.

4. Methodology

This section presents the methodology that was implemented in order to reach the results. It is divided into two topics. First, in Section 4.1., we analyze the predictive power of recommendations, compared to simple capitalizations of the current price. In Section 4.2. we look into the performance of actively managed portfolio, using analysts' recommendations.

4.1. Predictive power of recommendations

To analyze the predictive power of TP, we compare it to the predictive power of simply value of FP. We compare both as predictors with the real future market price after one year. We compare also FP to CP and TP to CP.

Initially, we would like to analyze the following three regressions:

$$FP_{it} = \alpha + \beta . TP_{it-52} + \varepsilon_{it} \quad , \tag{4}$$

$$FP_{it} = \alpha + \beta . CP_{it-52} + \varepsilon_{it} \quad , \tag{5}$$

$$TP_{it} = \alpha + \beta . CP_{it-52} + \varepsilon_{it} \quad . \tag{6}$$

But from Figure 1 we can see that the autocorrelation functions of our variables decay slowly to zero, meaning that we are facing non-stationary variables.

Despite what we mentioned earlier and to proof that our variables are non-stationary, we need to test if the variables have unit root (see Table 2). Where null hypothesis is the presence of unit root in data or data is not stationary and, alternative hypothesis is the inexistence of unit root or data is stationary. To decide, we know that if p-value >5% we accept null hypothesis; or, if p-value<5% we reject null hypothesis.

Figure 1 - Correlogram of ACF for FP(a), TP(b) and CP(c)

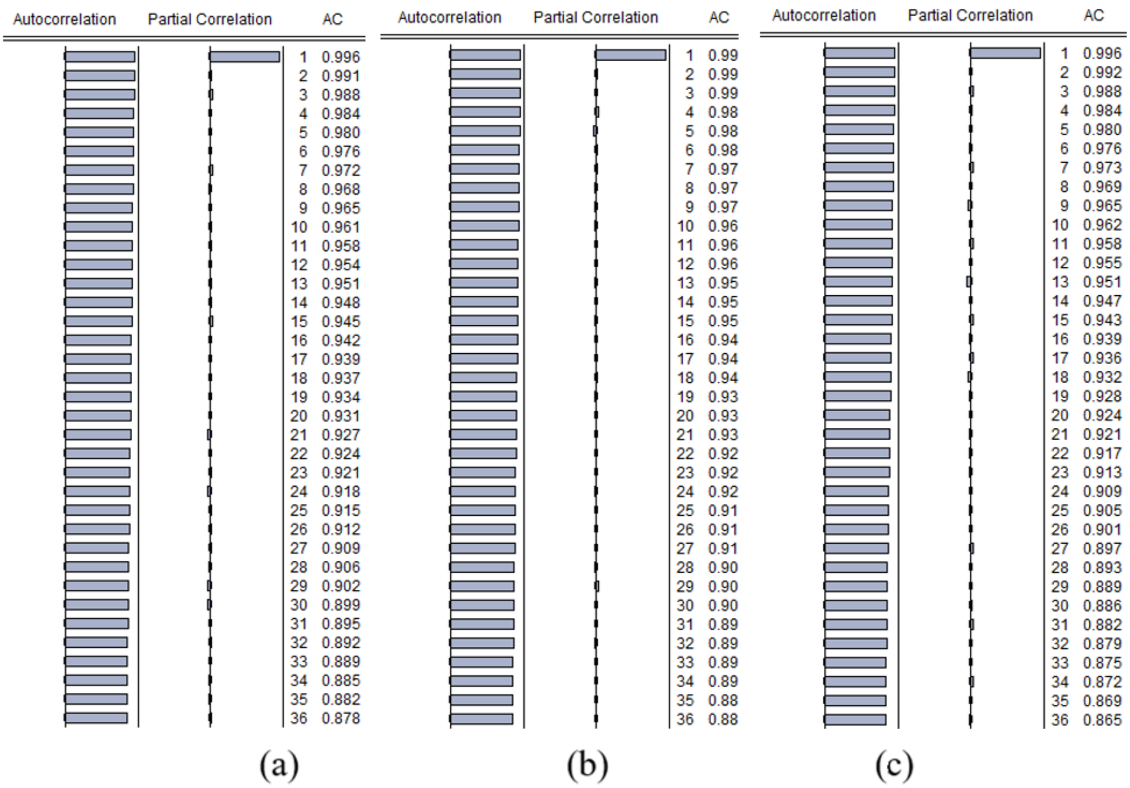


Table 2 - Unit Root Test

Method	FP Statistic	FP Prob.**	FP Cross-Section	FP Obs	TP Statistic	TP Prob.**	TP Cross-Section	TP Obs
Null: Unit root (assumes common unit root process)								
Levin, Lin & Chu t	6,755	1,000	50	36487	6,755	1,000	50	36487
Null: Unit root (assumes individual unit root process)								
Im, Pesaran and Shin W-stat	6,156	1,000	50	36487	6,156	1,000	50	36487
ADF-Fsher Chi-square	60,653	0,999	50	36487	60,653	0,999	50	36487
PP-Fisher Chi-square	57,242	1,000	50	36500	57,242	1,000	50	36500

Method	CP Statistic	CP Prob.**	CP Cross-Section	CP Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t	7,966	1,000	50	36303
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	8,492	1,000	50	36303
ADF-Fsher Chi-square	39,983	1,000	50	36303
PP-Fisher Chi-square	40,002	1,000	50	36500

**Probabilities for Fisher tests are computed using as asymptotic Chi-square distribution. All other tests assume asymptotic normality.

As our variables are non-stationary and to avoid spurious results, we use panel regression by first differences where we observe the variables for 50 companies with

731 observations for each. This panel data set is sometimes named as a "balanced panel data[2]" because we observe every single company over fourteen years.

$$\Delta FP_{it} = \alpha + \beta . \Delta TP_{it-52} + \varepsilon_{it} \quad , \tag{7}$$

$$\Delta FP_{it} = \alpha + \beta . \Delta CP_{it-52} + \varepsilon_{it} \quad , \tag{8}$$

$$\Delta TP_{it} = \alpha + \beta . \Delta CP_{it-52} + \varepsilon_{it} \quad . \tag{9}$$

4.2. Actively using analysts' recommendations

To analyze the performance of actively using analysts' recommendations we consider three different types of portfolios and the total return EURO STOXX 50® index itself as benchmark.

- The (naïve) homogeneous portfolio;
- Theoretical Mean-variance (MV), with and without short-selling;
- An active portfolio based upon analysts' recommendations;
- The EURO STOXX 50® index itself.

4.2.1. The (naïve) homogeneous portfolio

The (naïve) homogeneous portfolio for our 50 companies, keeps a small weight of 2% of the portfolio value invested in each stock, at each rebalancing date.

4.2.2. MV Tangent Portfolios

The idea of tangent portfolios comes from the Mean Variance Theory (MVT). According to this theory, investors act rationally with the goal of maximizing expected return for a given acceptable level of risk. So, we can focus the analysis on the so-called efficient frontier (EF) – the set of optimal portfolios for each risk level. From all efficient portfolio the tangent portfolio is the one with the maximal Sharpe ratio (SR).

[2] We use EViews platform to calculate the results for balanced panel data. Table A.1 in the appendix illustrates the panel data at a specific data point.

The Sharpe ratio[3] is a risk-adjusted return measure that is often used to compare the performance of investments.

So, the tangent portfolio is the Portfolio X that:

$$\begin{aligned} &\max_{X} \quad SR \\ &\text{s.t.}\, X \in EF \ . \end{aligned} \tag{10}$$

To determine the composition of tangent portfolios it is necessary to determine the so called MVT inputs, i.e., the vector of expected returns and the variance-covariance matrix:

$$\bar{R} = \begin{pmatrix} \bar{R}_1 \\ \bar{R}_2 \\ \vdots \\ \bar{R}_n \end{pmatrix} , \tag{11}$$

$$V = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_n^2 \end{pmatrix} . \tag{12}$$

When short selling is allowed the solution is given by:

$$x_i^T = \frac{z_i}{\sum_{j=1}^{n} z_j} , \tag{13}$$

where

$$Z = V^{-1}\tilde{R} \qquad \text{for} \qquad \tilde{R} = \bar{R} - R_f 1 \ . \tag{14}$$

When short selling is not allowed, we need to add inequality restrictions to problem (10) and the solution must be found numerically (using, for instance, Excel Solver).

The difference between the optimal without short selling to optimal with short selling portfolio is that in the last one negative weight are allowed. Meaning that we are opening a position by selling the portfolio first, assuming that in the future you are going to be able to buy it back for a cheaper price.

For the EURO STOXX 50® Index, we have considered it as benchmark.

[3] We calculate Sharpe ratio values based upon our 15-year period and taking Rf to be the 15-year risk free rate (4,418% from ECB).

Given the tangent portfolio and assuming borrowing is not allowed, MVT tells the EF has two branches. The investment line between the riskless asset F and the tangent portfolio T and, for volatility levels higher than σ_T, it is described by the upper part of the hyperbola that results from combining the risky assets:

$$\begin{cases} \bar{R}_p = R_f + \frac{\bar{R}_T - R_f}{\sigma_T}\sigma_{p,} & for\ \sigma < \sigma_T \\ \sigma_p^2 = \frac{A\bar{R}_p^2 - 2B\bar{R}_p + C}{AC - B^2}, & for\ \sigma \geq \sigma_T \end{cases}, \quad (15)$$

where A, B and C are the scalars:

$$A = 1'V^{-1}1 \ , \quad B = 1'V^{-1}\bar{R} \quad \text{and} \quad C = \bar{R}'V^{-1}\bar{R} \quad (16)$$

Table 3 - $\bar{R}$, sigma and Sharpe-ratio

	R bar	sigma	SR
Adidas	20,06%	27,49%	0,5690
Air Liquide	11,84%	19,86%	0,3737
Airbus	18,44%	32,71%	0,4285
Allianz	14,22%	30,73%	0,3189
Anheuser	16,80%	26,21%	0,4724
ASML	22,27%	29,73%	0,6004
Assicurazioni	5,32%	26,83%	0,0336
AXA	13,28%	37,63%	0,2356
Banco Bilbao	5,90%	34,10%	0,0433
Banco Santander	7,37%	32,76%	0,0901
BASF	15,53%	27,80%	0,3996
Bayer	13,58%	27,58%	0,3321
BNP Paribas	10,20%	36,55%	0,1583
BMW	12,31%	31,24%	0,2526
Danone	9,25%	19,43%	0,2488
Carrefour	1,15%	26,06%	-0,1256
Daimler	12,08%	34,57%	0,2217
Deutsche Bank	-2,32%	41,84%	-0,1611
Deutsche Post	11,08%	28,23%	0,2360
Deutsche Telekom	7,95%	21,39%	0,1650
E.ON	5,17%	28,52%	0,0265
ENEL	8,87%	23,29%	0,1912
ENI	8,09%	24,01%	0,1531
Essilor	13,22%	20,23%	0,4350
Fresenius	17,07%	25,37%	0,4986
Iberdrola	12,13%	24,63%	0,3131
Inditex	19,11%	25,75%	0,5705
ING	12,02%	45,93%	0,1656
Intesa Sanpaolo	10,97%	39,32%	0,1666
Philips	9,25%	27,44%	0,1762
L'Oreal	12,60%	19,86%	0,4119
LVMH	17,62%	25,49%	0,5179
Mucich RE	12,39%	22,08%	0,3610
Nokia	4,62%	37,55%	0,0053
Orange	6,41%	22,52%	0,0884
Repsol	8,38%	29,43%	0,1347
Safran	19,12%	29,69%	0,4953
Saint-Gobain	7,80%	32,54%	0,1039
Sanofi	8,26%	20,99%	0,1828
SAP	11,80%	24,07%	0,3068
Schneider Electric SE	13,70%	28,38%	0,3272
Siemens	10,70%	29,32%	0,2142
Societe Generale	7,17%	43,90%	0,0627
Telefonica	4,56%	22,75%	0,0060
Total	9,24%	21,99%	0,2190
Unicredit	0,37%	49,22%	-0,0823
Unilever	11,90%	18,52%	0,4040
Vinci	17,07%	26,09%	0,4849
Vivendi	9,27%	22,59%	0,2146
Volkswagen	21,59%	37,40%	0,4592

Table 4 - Correlation between companies

	Adidas	Air Liquide	Airbus	Allianz	Anheuser	ASML	Assicurazioni	AXA	Banco Bilbao	Banco Santand	BASF	Bayer	BNP Paribas	BMW	Danone	Carrefour	Daimler
Adidas	1,000																
Air Liquide	0,510	1,000															
Airbus	0,380	0,475	1,000														
Allianz	0,584	0,639	0,431	1,000													
Anheuser	0,338	0,396	0,310	0,367	1,000												
ASML	0,369	0,457	0,480	0,430	0,291	1,000											
Assicurazioni	0,410	0,544	0,349	0,633	0,286	0,370	1,000										
AXA	0,542	0,627	0,451	0,861	0,317	0,419	0,704	1,000									
Banco Bilbao	0,455	0,555	0,393	0,711	0,334	0,405	0,707	0,754	1,000								
Banco Santander	0,448	0,557	0,403	0,720	0,357	0,407	0,700	0,741	0,918	1,000							
BASF	0,579	0,736	0,475	0,748	0,419	0,477	0,553	0,690	0,644	0,632	1,000						
Bayer	0,457	0,586	0,378	0,518	0,343	0,428	0,469	0,498	0,483	0,480	0,624	1,000					
BNP Paribas	0,444	0,508	0,377	0,700	0,281	0,390	0,645	0,755	0,750	0,758	0,592	0,462	1,000				
BMW	0,550	0,625	0,481	0,643	0,390	0,459	0,486	0,649	0,559	0,567	0,731	0,518	0,572	1,000			
Danone	0,380	0,492	0,383	0,372	0,413	0,325	0,359	0,363	0,353	0,374	0,420	0,447	0,336	0,388	1,000		
Carrefour	0,336	0,432	0,356	0,424	0,280	0,353	0,465	0,472	0,466	0,452	0,422	0,338	0,497	0,407	0,397	1,000	
Daimler	0,586	0,652	0,529	0,702	0,370	0,496	0,510	0,680	0,604	0,587	0,758	0,526	0,539	0,816	0,388	0,428	1,000
Deutsche Bank	0,518	0,563	0,390	0,779	0,323	0,400	0,609	0,756	0,723	0,722	0,698	0,493	0,736	0,644	0,323	0,408	0,652
Deutsche Post	0,527	0,590	0,435	0,681	0,355	0,407	0,516	0,653	0,600	0,586	0,695	0,522	0,505	0,611	0,348	0,369	0,655
Deutsche Telekom	0,369	0,465	0,371	0,484	0,303	0,362	0,454	0,426	0,442	0,453	0,473	0,469	0,402	0,407	0,377	0,382	0,427
E.ON	0,439	0,515	0,363	0,580	0,334	0,342	0,522	0,544	0,568	0,561	0,621	0,510	0,454	0,466	0,362	0,386	0,525
ENEL	0,399	0,546	0,371	0,524	0,311	0,331	0,659	0,584	0,631	0,595	0,546	0,449	0,515	0,443	0,409	0,446	0,495
ENI	0,470	0,614	0,456	0,566	0,370	0,416	0,631	0,590	0,608	0,597	0,661	0,550	0,551	0,553	0,424	0,460	0,571
Essilor	0,289	0,439	0,366	0,282	0,361	0,305	0,325	0,308	0,294	0,294	0,370	0,373	0,294	0,313	0,403	0,360	0,303
Fresenius	0,302	0,352	0,309	0,313	0,256	0,310	0,299	0,281	0,241	0,229	0,366	0,382	0,240	0,260	0,300	0,246	0,307
Iberdrola	0,424	0,559	0,345	0,596	0,338	0,365	0,605	0,598	0,693	0,674	0,575	0,450	0,512	0,469	0,409	0,429	0,523
Inditex	0,477	0,485	0,388	0,520	0,349	0,410	0,473	0,511	0,522	0,519	0,467	0,397	0,459	0,462	0,419	0,420	0,491
ING	0,516	0,598	0,400	0,790	0,363	0,394	0,650	0,819	0,756	0,740	0,707	0,508	0,723	0,611	0,293	0,417	0,647
Intesa Sanpaolo	0,429	0,509	0,363	0,699	0,300	0,364	0,744	0,757	0,789	0,771	0,608	0,463	0,719	0,530	0,311	0,437	0,572
Philips	0,508	0,580	0,511	0,640	0,453	0,575	0,500	0,628	0,601	0,581	0,646	0,548	0,576	0,585	0,422	0,437	0,633
L'Oreal	0,427	0,576	0,385	0,477	0,386	0,418	0,414	0,462	0,458	0,442	0,528	0,492	0,391	0,461	0,620	0,450	0,491
LVMH	0,585	0,651	0,525	0,625	0,370	0,517	0,485	0,608	0,524	0,523	0,653	0,531	0,543	0,650	0,483	0,446	0,680
Mucich RE	0,476	0,565	0,411	0,783	0,336	0,407	0,599	0,717	0,602	0,596	0,647	0,496	0,602	0,573	0,375	0,409	0,606
Nokia	0,294	0,343	0,300	0,388	0,224	0,378	0,358	0,405	0,380	0,393	0,368	0,339	0,372	0,395	0,268	0,306	0,401
Orange	0,299	0,448	0,311	0,435	0,264	0,299	0,474	0,418	0,446	0,454	0,390	0,406	0,387	0,357	0,396	0,390	0,381
Repsol	0,447	0,581	0,394	0,589	0,318	0,401	0,587	0,595	0,680	0,690	0,635	0,496	0,588	0,549	0,373	0,404	0,566
Safran	0,427	0,526	0,592	0,473	0,264	0,457	0,382	0,495	0,416	0,404	0,532	0,436	0,420	0,542	0,358	0,312	0,567
Saint-Gobain	0,568	0,630	0,526	0,720	0,333	0,528	0,588	0,758	0,663	0,652	0,713	0,526	0,669	0,687	0,421	0,470	0,738
Sanofi	0,267	0,450	0,368	0,365	0,328	0,344	0,387	0,370	0,357	0,368	0,388	0,474	0,340	0,391	0,407	0,384	0,367
SAP	0,489	0,568	0,390	0,572	0,323	0,449	0,420	0,526	0,444	0,420	0,582	0,478	0,427	0,537	0,420	0,341	0,608
Schneider Electric SE	0,526	0,668	0,520	0,639	0,365	0,478	0,563	0,656	0,604	0,586	0,687	0,520	0,601	0,651	0,449	0,458	0,685
Siemens	0,579	0,653	0,486	0,727	0,352	0,510	0,536	0,682	0,626	0,615	0,761	0,554	0,553	0,671	0,412	0,398	0,722
Societe Generale	0,450	0,484	0,343	0,718	0,364	0,357	0,658	0,759	0,757	0,764	0,603	0,430	0,830	0,554	0,277	0,454	0,550
Telefonica	0,399	0,579	0,380	0,601	0,339	0,373	0,617	0,577	0,693	0,708	0,549	0,501	0,537	0,499	0,435	0,434	0,523
Total	0,473	0,659	0,473	0,551	0,360	0,442	0,562	0,562	0,583	0,582	0,669	0,574	0,546	0,561	0,461	0,457	0,582
Unicredit	0,397	0,475	0,350	0,629	0,235	0,314	0,681	0,718	0,752	0,735	0,557	0,436	0,711	0,502	0,256	0,420	0,529
Unilever	0,405	0,499	0,350	0,371	0,420	0,360	0,361	0,350	0,367	0,369	0,428	0,429	0,303	0,368	0,638	0,375	0,381
Vinci	0,540	0,622	0,466	0,631	0,295	0,444	0,553	0,659	0,607	0,575	0,652	0,458	0,567	0,588	0,386	0,446	0,670
Vivendi	0,397	0,551	0,420	0,554	0,253	0,412	0,542	0,555	0,535	0,520	0,520	0,469	0,488	0,464	0,412	0,419	0,514
Volkswagen	0,360	0,376	0,305	0,408	0,251	0,347	0,379	0,419	0,390	0,393	0,457	0,369	0,375	0,559	0,296	0,289	0,544

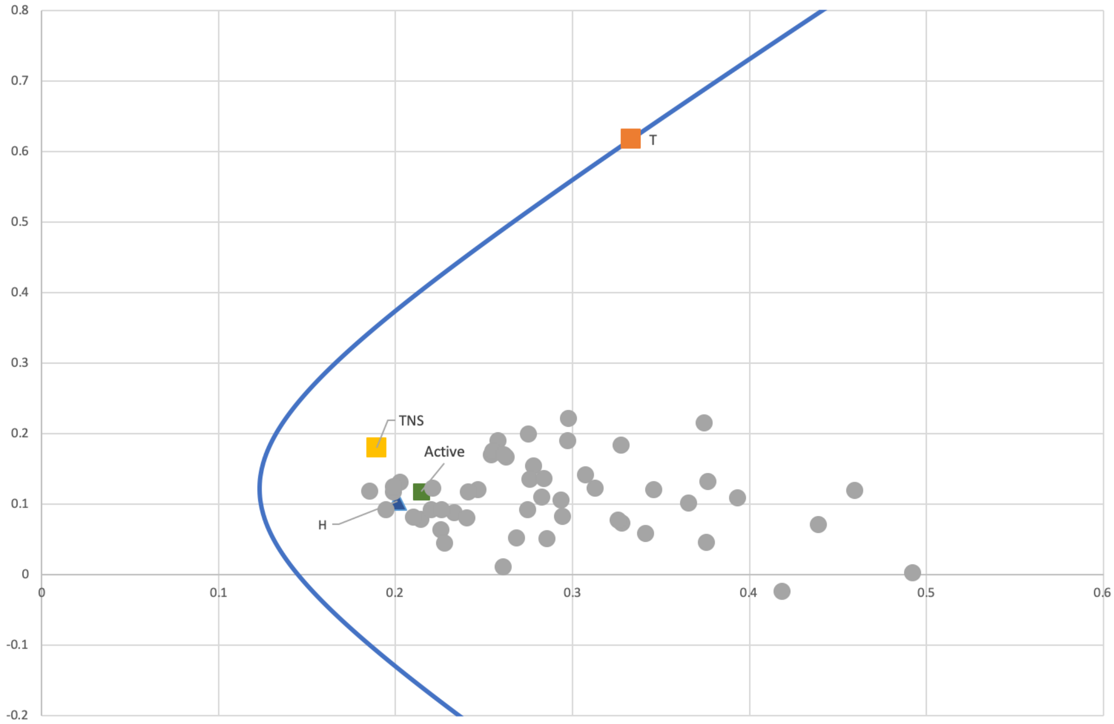
	Deutsche Bank	Deutsche Post	Deutsche Telek	E.ON	ENEL	ENI	Essilor	Fresenius	Iberdrola	Inditex	ING	Intesa Sanpaol	Philips	L'Oreal	LVMH	Mucich RE
Deutsche Bank	1,000															
Deutsche Post	0,610	1,000														
Deutsche Telekom	0,425	0,465	1,000													
E.ON	0,543	0,547	0,486	1,000												
ENEL	0,480	0,500	0,477	0,610	1,000											
ENI	0,552	0,560	0,457	0,595	0,628	1,000										
Essilor	0,286	0,237	0,297	0,290	0,338	0,353	1,000									
Fresenius	0,265	0,288	0,303	0,308	0,277	0,332	0,353	1,000								
Iberdrola	0,520	0,526	0,460	0,608	0,680	0,568	0,307	0,280	1,000							
Inditex	0,438	0,473	0,369	0,392	0,442	0,467	0,352	0,287	0,466	1,000						
ING	0,754	0,660	0,385	0,548	0,567	0,568	0,296	0,250	0,591	0,486	1,000					
Intesa Sanpaolo	0,724	0,575	0,413	0,541	0,648	0,590	0,233	0,214	0,602	0,459	0,746	1,000				
Philips	0,603	0,573	0,460	0,519	0,477	0,553	0,346	0,361	0,497	0,501	0,637	0,546	1,000			
L'Oreal	0,404	0,476	0,447	0,426	0,469	0,467	0,419	0,312	0,496	0,481	0,412	0,396	0,523	1,000		
LVMH	0,559	0,545	0,400	0,459	0,457	0,564	0,410	0,324	0,462	0,555	0,569	0,502	0,616	0,624	1,000	
Mucich RE	0,625	0,565	0,472	0,504	0,478	0,535	0,310	0,323	0,538	0,469	0,654	0,576	0,602	0,460	0,553	1,000
Nokia	0,357	0,335	0,290	0,317	0,331	0,351	0,164	0,156	0,389	0,367	0,380	0,341	0,381	0,350	0,388	0,320
Orange	0,366	0,393	0,678	0,416	0,507	0,418	0,291	0,241	0,493	0,357	0,364	0,446	0,413	0,463	0,406	0,422
Repsol	0,555	0,558	0,434	0,568	0,539	0,734	0,284	0,251	0,620	0,469	0,573	0,580	0,519	0,442	0,529	0,499
Safran	0,435	0,474	0,335	0,359	0,383	0,462	0,326	0,336	0,384	0,413	0,476	0,381	0,554	0,446	0,542	0,440
Saint-Gobain	0,677	0,644	0,440	0,503	0,558	0,593	0,319	0,276	0,559	0,540	0,710	0,657	0,656	0,512	0,687	0,621
Sanofi	0,310	0,340	0,458	0,372	0,390	0,452	0,356	0,308	0,372	0,340	0,311	0,328	0,427	0,437	0,401	0,373
SAP	0,521	0,475	0,368	0,434	0,412	0,509	0,254	0,306	0,417	0,431	0,498	0,450	0,551	0,469	0,577	0,502
Schneider Electric SE	0,591	0,580	0,403	0,471	0,543	0,582	0,359	0,322	0,520	0,565	0,638	0,565	0,636	0,525	0,677	0,571
Siemens	0,666	0,671	0,473	0,579	0,535	0,610	0,291	0,351	0,570	0,520	0,646	0,592	0,693	0,521	0,678	0,611
Societe Generale	0,752	0,550	0,400	0,513	0,533	0,552	0,266	0,221	0,559	0,458	0,773	0,759	0,592	0,355	0,500	0,619
Telefonica	0,542	0,526	0,587	0,536	0,584	0,583	0,319	0,278	0,670	0,488	0,532	0,594	0,504	0,494	0,488	0,562
Total	0,539	0,540	0,468	0,580	0,592	0,855	0,381	0,332	0,549	0,443	0,521	0,532	0,564	0,514	0,598	0,520
Unicredit	0,704	0,526	0,371	0,468	0,585	0,548	0,239	0,188	0,528	0,400	0,745	0,820	0,516	0,347	0,439	0,514
Unilever	0,307	0,377	0,411	0,404	0,399	0,455	0,373	0,300	0,393	0,411	0,324	0,305	0,461	0,617	0,465	0,367
Vinci	0,584	0,583	0,417	0,512	0,600	0,588	0,326	0,286	0,585	0,505	0,613	0,601	0,577	0,489	0,626	0,543
Vivendi	0,489	0,480	0,477	0,470	0,530	0,514	0,319	0,311	0,499	0,440	0,491	0,507	0,533	0,478	0,523	0,508
Volkswagen	0,402	0,396	0,266	0,322	0,332	0,357	0,182	0,198	0,350	0,376	0,399	0,379	0,399	0,367	0,468	0,355

	Nokia	Orange	Repsol	Safran	Saint-Gobain	Sanofi	SAP	Schneider Elect	Siemens	Societe Genera	Telefonica	Total	Unicredit	Unilever	Vinci	Vivendi	Volkswagen
Nokia	1,000																
Orange	0,356	1,000															
Repsol	0,385	0,394	1,000														
Safran	0,326	0,279	0,446	1,000													
Saint-Gobain	0,399	0,423	0,562	0,548	1,000												
Sanofi	0,255	0,377	0,362	0,333	0,349	1,000											
SAP	0,335	0,355	0,429	0,445	0,575	0,339	1,000										
Schneider Electric SE	0,385	0,379	0,578	0,556	0,759	0,371	0,568	1,000									
Siemens	0,398	0,422	0,585	0,542	0,732	0,368	0,615	0,684	1,000								
Societe Generale	0,336	0,377	0,562	0,361	0,635	0,316	0,415	0,562	0,573	1,000							
Telefonica	0,360	0,668	0,653	0,370	0,546	0,381	0,437	0,513	0,552	0,538	1,000						
Total	0,361	0,440	0,731	0,447	0,594	0,461	0,510	0,614	0,632	0,518	0,570	1,000					
Unicredit	0,318	0,390	0,514	0,387	0,618	0,264	0,388	0,517	0,535	0,743	0,536	0,478	1,000				
Unilever	0,257	0,379	0,398	0,390	0,361	0,500	0,388	0,387	0,401	0,270	0,431	0,459	0,260	1,000			
Vinci	0,387	0,438	0,529	0,503	0,762	0,335	0,527	0,692	0,649	0,546	0,523	0,592	0,546	0,368	1,000		
Vivendi	0,335	0,514	0,457	0,442	0,567	0,440	0,445	0,550	0,546	0,475	0,548	0,515	0,460	0,417	0,571	1,000	
Volkswagen	0,316	0,250	0,415	0,387	0,444	0,228	0,375	0,484	0,442	0,385	0,356	0,342	0,371	0,260	0,408	0,353	1,000

Table 3 and Table 4 present MVT inputs: the vector of expected returns and correlations between our companies, respectively.

Figure 2 illustrates the MV representation (tangent with short selling), other 3 portfolios and 50 all stocks under analysis.

Figure 2 - Efficient frontier, portfolios and individual companies



H – Homogeneous; T – Tangent with short selling; TNS – Tangent no short selling

As Markowitz studied, an investor with the ability to invest in risky assets wants to build a portfolio with the lowest possible risk for a given expected return.

For the Markowitz (1952) criterion, any portfolio that stay out of the efficient frontier is consider sub-optimal because exists much risk relative to its return or too little return relative to its risk.

In Table 5 we present the composition of our passive portfolios. And as we can see, all portfolios are below the EF. This means that any of these portfolios provide enough return when compared to the level of risk, implying that any portfolios are efficient concluding that none of these combinations are the best.

Table 5 - Passive portfolios composition

	H	TNS	T
Adidas	2,00%	15,72%	30,38%
Air Liquide	2,00%	0,00%	-7,20%
Airbus	2,00%	0,00%	11,93%
Allianz	2,00%	0,00%	22,45%
Anheuser	2,00%	12,64%	25,09%
ASML	2,00%	20,18%	41,35%
Assicurazioni	2,00%	0,00%	-33,26%
AXA	2,00%	0,00%	19,17%
Banco Bilbao	2,00%	0,00%	-25,31%
Banco Santander	2,00%	0,00%	21,40%
BASF	2,00%	0,00%	41,19%
Bayer	2,00%	0,00%	10,46%
BNP Paribas	2,00%	0,00%	30,79%
BMW	2,00%	0,00%	0,28%
Danone	2,00%	0,00%	-28,12%
Carrefour	2,00%	0,00%	-40,27%
Daimler	2,00%	0,00%	-26,35%
Deutsche Bank	2,00%	0,00%	-56,05%
Deutsche Post	2,00%	0,00%	-0,99%
Deutsche Telekom	2,00%	0,00%	7,68%
E.ON	2,00%	0,00%	-25,77%
ENEL	2,00%	0,00%	-2,57%
ENI	2,00%	0,00%	-16,88%
Essilor	2,00%	8,41%	15,29%
Fresenius	2,00%	18,13%	16,76%
Iberdrola	2,00%	0,00%	37,79%
Inditex	2,00%	14,43%	35,26%
ING	2,00%	0,00%	-2,02%
Intesa Sanpaolo	2,00%	0,00%	40,90%
Philips	2,00%	0,00%	-38,14%
L'Oreal	2,00%	0,00%	7,68%
LVMH	2,00%	0,00%	18,51%
Mucich RE	2,00%	0,00%	25,20%
Nokia	2,00%	0,00%	-17,52%
Orange	2,00%	0,00%	3,03%
Repsol	2,00%	0,00%	-12,72%
Safran	2,00%	2,91%	15,05%
Saint-Gobain	2,00%	0,00%	-66,73%
Sanofi	2,00%	0,00%	-15,39%
SAP	2,00%	0,00%	6,84%
Schneider Electric SE	2,00%	0,00%	-2,48%
Siemens	2,00%	0,00%	-17,02%
Societe Generale	2,00%	0,00%	-7,70%
Telefonica	2,00%	0,00%	-43,15%
Total	2,00%	0,00%	15,87%
Unicredit	2,00%	0,00%	-12,36%
Unilever	2,00%	0,00%	17,40%
Vinci	2,00%	0,00%	57,34%
Vivendi	2,00%	0,00%	1,09%
Volkswagen	2,00%	7,57%	21,82%

4.2.3. The active (recommendation based) portfolio

For the active portfolio, we purpose weights to be determined (at each rebalancing date):

$$w_{it} = \frac{Price\ spread\ _{it}}{\sum_{i=1}^{50} Price\ Spread\ _{it}}\ , \tag{17}$$

where the price spread value is provided by Bloomberg and is nothing but the difference between the 12M Tgt Px and the stock current price:

$$Price\ Spread_t = 12M\ Tgt\ Px_t - Price_t\ . \qquad (18)$$

Note that the weights formula (17) gives us the respective percentage of each company compared to a total of price spreads. Companies with high spread have high weight comparing with companies with lower price spread, and negative price spreads had to short-selling positions. These will be short-selling positions only where the real price in the market exceeds the recommendation price given by analysts. Positive weights tell us that the recommendation price exceeds the real price in the market.

Figure 3 - Active portfolio composition evolution (annual)

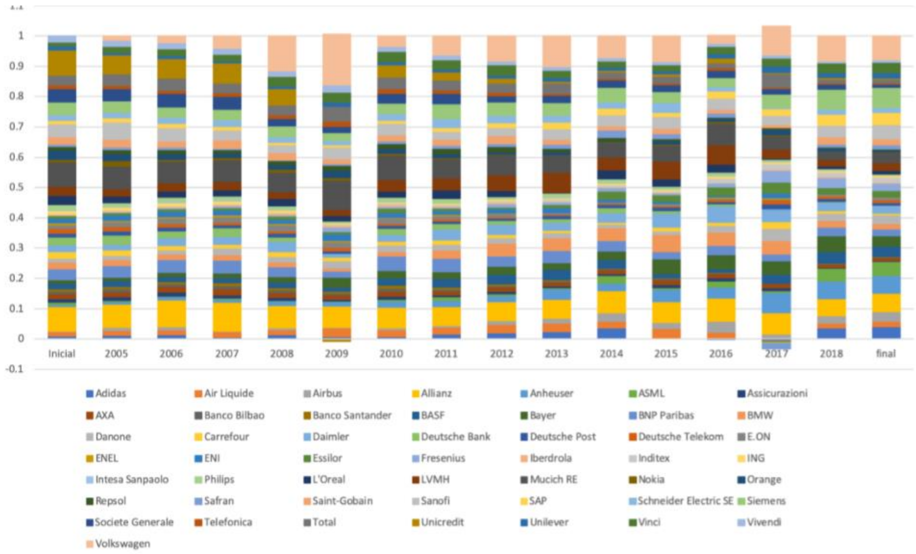


Figure 3 is based on Table A.2 in the Appendix. This figure shows the active portfolio composition evolution in annual terms by each company.

4.2.4. Rebalancing schemes

We simulate an investment of 1000€ at beginning of our sample (27/04/2004), to increase the robustness of our results, we also consider five different rebalancing schemes in each of the three mentioned types portfolios (homogeneous, active and tangent):

1. Full;
2. Monthly;

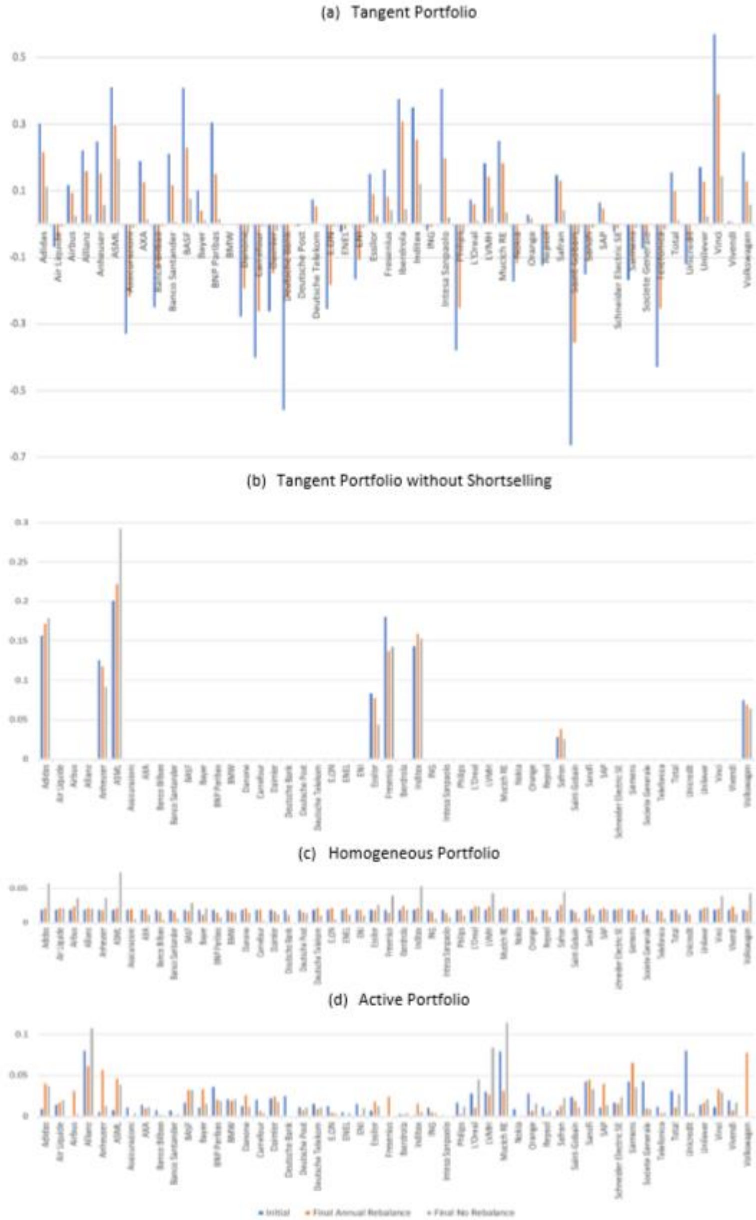
3. Semi-annual;

4. Annual;

5. No rebalance.

For robustness we decide to present the initial and final compositions of our portfolios. In Figure 4 we just present final compositions for annual rebalance and no rebalance terms.

Figure 4 - Initial and Final compositions



We can see better in Figures A.1 to A.4 in the Appendix how is the variation in the composition of each portfolio depending on the rebalancing strategy used.

5. Results

In this chapter we present and discuss the results of our analysis. We start by looking at the (absence of) predictive power of recommendations, then we so on into portfolio analysis over our 15-year sample period.

5.1. Results for predictive power of recommendations

Before proceeding to results, we decide to present, in illustrative terms, individual regressions in the composition of tangent portfolio without short selling. In the following tables we can conclude, as previously discussed in the methodology Section, that all our variables are not stationary. Thus, the results for level regressions are not meaningful and can be interpreted as spurious.

However, is important to refer that Volkswagen observations are less than the other companies because we just have data from 2006 in levels and from 2009 in differences.

Table 6 - Individual regressions in Levels (Y=FP, X=TP) (a) and in differences (Y=ΔFP, X=ΔTP) (b)

(a)

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0,9132	0,9245	0,9566	0,9489	0,9143	0,9391	0,9584	0,5404
R Square	0,8339	0,8547	0,9151	0,9004	0,8359	0,8818	0,9185	0,2921
Adjusted R Square	0,8336	0,8545	0,9150	0,9003	0,8357	0,8817	0,9184	0,2910
Standard Error	23,0141	11,6967	14,1228	10,2800	8,7074	3,3725	8,6591	41,2734
Observations	731	731	731	731	731	731	731	679
Intercept								
Coefficient	-6,5788	3,2317	-1,3111	2,7221	3,6783	1,2282	-7,0116	46,9403
Standard Error	1,5922	0,8641	0,8400	0,8709	0,5775	0,2310	0,5916	4,2281
t Stat	-4,1318	3,7398	-1,5608	3,1255	6,3691	5,3175	-11,8514	11,1019
P-value	0,0000	0,0002	0,1190	0,0018	0,0000	0,0000	0,0000	0,0000
Lower 95%	-9,7048	1,5352	-2,9602	1,0123	2,5445	0,7748	-8,1731	38,6385
Upper 95%	-3,4529	4,9283	0,3381	4,4319	4,8121	1,6817	-5,8501	55,2421
TP Variable								
Coefficient	1,11674	0,8049	1,1506	0,92250	0,85320	0,84368	1,22150	0,45112
Standard Error	0,01846	0,0123	0,0130	0,01136	0,01400	0,01144	0,01348	0,02699
t Stat	60,49174	65,4910	88,6353	81,19745	60,94777	73,75920	90,64759	16,71201
P-value	0,00000	0,0000	0,0000	0,00000	0,00000	0,00000	0,00000	0,00000
Lower 95%	1,08049	0,7808	1,1251	0,90020	0,82572	0,82123	1,19505	0,39812
Upper 95%	1,15298	0,8290	1,1761	0,94481	0,88068	0,86614	1,24796	0,50413
ANOVA								
SS	1938121,5127	586797,3605	1566947,1621	696736,6146	281639,8382	61877,8374	616104,0107	475770,5434
MS	1938121,5127	586797,3605	1566947,1621	696736,6146	281639,8382	61877,8374	616104,0107	475770,5434
F	3659,2505	4289,0686	7856,2240	6593,0259	3714,6310	5440,4201	8216,9853	279,2912
Significance F	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

(b)

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0,0124	0,0812	0,0297	0,0345	0,0137	0,0012	0,1157	0,0488
R Square	0,0002	0,0066	0,0009	0,0012	0,0002	0,0000	0,0134	0,0024
Adjusted R Square	-0,0012	0,0052	-0,0005	-0,0002	-0,0012	-0,0014	0,0120	0,0002
Standard Error	3,1255	0,7287	2,6244	2,1335	1,3584	0,5834	1,5236	6,4974
Observations	730	730	730	730	730	730	730	470
Intercept								
Coefficient	0,2757	0,1192	0,2204	0,1055	0,0616	0,0336	0,1223	0,1998
Standard Error	0,1174	0,0682	0,0992	0,0800	0,0511	0,0218	0,0573	0,2999
t Stat	2,3488	1,7493	2,2227	1,3178	1,2048	1,5381	2,1327	0,6662
P-value	0,0191	0,0807	0,0265	0,1880	0,2287	0,1245	0,0333	0,5056
Lower 95%	0,0452	-0,0146	0,0257	-0,0517	-0,0388	-0,0093	0,0097	-0,3895
Upper 95%	0,5061	0,2530	0,4150	0,2626	0,1619	0,0765	0,2348	0,7890
DTP Variable								
Coefficient	0,0255	-0,2023	0,0737	0,0931	-0,0352	-0,0030	0,3207	0,0622
Standard Error	0,0760	0,0920	0,0918	0,0999	0,0955	0,0914	0,1020	0,0589
t Stat	0,3356	-2,1989	0,8029	0,9317	-0,3690	-0,0328	3,1430	1,0563
P-value	0,7373	0,0282	0,4223	0,3518	0,7122	0,9738	0,0017	0,2914
Lower 95%	-0,1237	-0,3828	-0,1066	-0,1031	-0,2226	-0,1825	0,1204	-0,0535
Upper 95%	0,1746	-0,0217	0,2540	0,2894	0,1522	0,1765	0,5211	0,1780
ANOVA								
SS	1,1000	15,9185	4,4402	3,9518	0,2513	0,0004	22,9319	47,1055
MS	1,1000	15,9185	4,4402	3,9518	0,2513	0,0004	22,9319	47,1055
F	0,1126	4,8350	0,6447	0,8682	0,1362	0,0011	9,8782	1,1158
Significance F	0,7373	0,0282	0,4223	0,3518	0,7122	0,9738	0,0017	0,2914

Table 7 - Individual regressions in Levels (Y=FP, X=CP) (a) and in differences (Y=ΔFP, X=ΔCP) (b)

(a)

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0,9404	0,9262	0,9566	0,9487	0,9328	0,9448	0,9697	0,7627
R Square	0,8843	0,8579	0,9150	0,9000	0,8702	0,8927	0,9402	0,5818
Adjusted R Square	0,8841	0,8577	0,9149	0,8999	0,8700	0,8925	0,9402	0,5811
Standard Error	19,2060	11,5670	14,1260	10,3022	7,7464	3,2140	7,4152	31,7240
Observations	731	731	731	731	731	731	731	679
Intercept								
Coefficient	2,1830	9,2317	3,0541	7,5376	5,1339	2,4446	-1,0466	39,3794
Standard Error	1,2048	0,7764	0,8022	0,8199	0,4897	0,2062	0,4568	2,6745
t Stat	1,8119	11,8897	3,8071	9,1934	10,4831	11,8543	-2,2909	14,7239
P-value	0,0704	0,0000	0,0002	0,0000	0,0000	0,0000	0,0223	0,0000
Lower 95%	-0,1823	7,7074	1,4792	5,9280	4,1725	2,0397	-1,9434	34,1281
Upper 95%	4,5483	10,7560	4,6291	9,1473	6,0954	2,8494	-0,1497	44,6308
CP Variable								
Coefficient	0,97466	0,7703	0,9547	0,8697	0,8087	0,7918	1,0556	0,5835
Standard Error	0,01306	0,0116	0,0108	0,0107	0,0116	0,0102	0,0099	0,0190
t Stat	74,64542	66,3494	88,6132	81,0032	69,8970	77,8717	107,0977	30,6864
P-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Lower 95%	0,9490	0,7475	0,9335	0,8487	0,7860	0,7718	1,0363	0,5461
Upper 95%	1,0003	0,7931	0,9758	0,8908	0,8315	0,8118	1,0750	0,6208
ANOVA								
SS	2055328,9972	588997,2164	1566880,7941	696403,7535	293167,2303	62638,9782	630679,4665	947693,5981
MS	2055328,9972	588997,2164	1566880,7941	696403,7535	293167,2303	62638,9782	630679,4665	947693,5981
F	5571,9389	4402,2472	7852,3071	6561,5259	4885,5951	6064,0068	11469,9111	941,6548
Significance F	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

(b)

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0,0387	0,0390	0,0223	0,0021	0,0246	0,1010	0,0432	0,1214
R Square	0,0015	0,0015	0,0005	0,0000	0,0006	0,0102	0,0019	0,0147
Adjusted R Square	0,0001	0,0002	-0,0009	-0,0014	-0,0008	0,0088	0,0005	0,0126
Standard Error	3,1234	1,8191	2,6249	2,1348	1,3581	0,5805	1,5325	6,4570
Observations	730	730	730	730	730	730	730	470
Intercept								
Coefficient	0,2714	0,0976	0,2309	0,1173	0,0605	0,0303	0,1493	0,1773
Standard Error	0,1161	0,0674	0,0976	0,0792	0,0504	0,0215	0,0569	0,2981
t Stat	2,3382	1,4480	2,3659	1,4817	1,1999	1,4061	2,6235	0,5948
P-value	0,0196	0,1480	0,0182	0,1389	0,2306	0,1601	0,0089	0,5523
Lower 95%	0,0435	-0,0347	0,0393	-0,0381	-0,0385	-0,0120	0,0376	-0,4085
Upper 95%	0,4993	0,2300	0,4224	0,2727	0,1594	0,0725	0,2611	0,7631
DCP Variable								
Coefficient	0,0365	-0,0356	0,0224	0,0020	-0,0249	0,0924	0,0446	0,1026
Standard Error	0,0349	0,0337	0,0373	0,0350	0,0376	0,0337	0,0382	0,0388
t Stat	1,0460	-1,0539	0,6015	0,0571	-0,6629	2,7390	1,1676	2,6450
P-value	0,2959	0,2923	0,5477	0,9545	0,5076	0,0063	0,2434	0,0084
Lower 95%	-0,0320	-0,1018	-0,0508	-0,0668	-0,0988	0,0262	-0,0304	0,0264
Upper 95%	0,1051	0,0307	0,0957	0,0708	0,0489	0,1586	0,1196	0,1788
ANOVA								
SS	10,6731	3,6758	2,4931	0,0149	0,8105	2,5277	3,2016	291,6781
MS	10,6731	3,6758	2,4931	0,0149	0,8105	2,5277	3,2016	291,6781
F	1,0941	1,1108	0,3618	0,0033	0,4394	7,5019	1,3632	6,9958
Significance F	0,2959	0,2923	0,5477	0,9545	0,5076	0,0063	0,2434	0,0084

Table 8 - Individual regressions in Levels (Y=FP, X=CP) (a) and in differences (Y=ΔFP, X=ΔCP) (b)

(a)

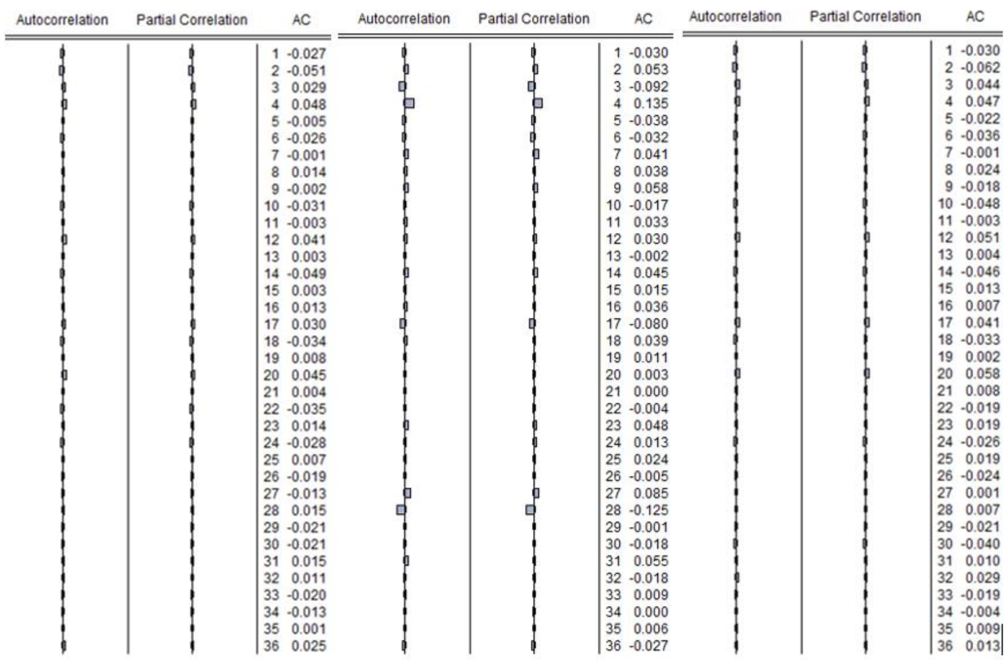
	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0,9907	0,9947	0,9944	0,9910	0,9927	0,9926	0,9909	0,8291
R Square	0,9816	0,9895	0,9889	0,9820	0,9855	0,9852	0,9819	0,6875
Adjusted R Square	0,9815	0,9895	0,9889	0,9820	0,9855	0,9852	0,9819	0,6870
Standard Error	6,2686	3,6153	4,2426	4,4920	2,7701	1,3281	3,2030	32,8506
Observations	731	731	731	731	731	731	731	679
Intercept								
Coefficient	10,3126	7,8353	4,0534	5,7802	2,5836	1,6513	5,5437	50,0617
Standard Error	0,3932	0,2427	0,2409	0,3575	0,1751	0,0852	0,1973	2,7695
t Stat	26,2256	32,2865	16,8234	16,1686	14,7528	19,3773	28,0942	18,0760
P-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Lower 95%	9,5406	7,3589	3,5804	5,0784	2,2398	1,4840	5,1563	44,6238
Upper 95%	11,0845	8,3118	4,5264	6,4821	2,9274	1,8186	5,9311	55,4995
CP Variable								
Coefficient	0,8397	0,9501	0,8251	0,9345	0,9223	0,9259	0,8464	0,7598
Standard Error	0,0043	0,0036	0,0032	0,0047	0,0041	0,0042	0,0043	0,0197
t Stat	197,0290	261,8558	255,0016	199,6117	222,9159	220,3481	198,7974	38,5915
P-value	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
Lower 95%	0,8313	0,9430	0,8188	0,9253	0,9142	0,9176	0,8380	0,7212
Upper 95%	0,8480	0,9573	0,8315	0,9437	0,9305	0,9341	0,8548	0,7985
ANOVA								
SS	1525452,8006	896220,5008	1170423,2875	804002,8344	381300,1144	85645,5716	405439,6879	1607205,2309
MS	1525452,8006	896220,5008	1170423,2875	804002,8344	381300,1144	85645,5716	405439,6879	1607205,2309
F	38820,4085	68568,4530	65025,7907	39844,8494	49691,4882	48553,2918	39520,4245	1489,3063
Significance F	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000

(b)

	Adidas	Anheuser	ASML	Essilor	Fresenius	Inditex	Safran	Volkswagen
Regression Statistics								
Multiple R	0,3695	0,2876	0,2176	0,1779	0,0904	0,1263	0,2184	0,2012
R Square	0,1366	0,0827	0,0473	0,0316	0,0082	0,0159	0,0477	0,0405
Adjusted R Square	0,1354	0,0815	0,0460	0,0303	0,0068	0,0146	0,0464	0,0384
Standard Error	1,4169	0,7002	1,0338	0,7785	0,5253	0,2346	0,5400	4,9930
Observations	730	730	730	730	730	730	730	470
Intercept								
Coefficient	0,2103	0,1147	0,1950	0,1214	0,0936	0,0346	0,0914	0,1243
Standard Error	0,0527	0,0260	0,0384	0,0289	0,0195	0,0087	0,0201	0,2305
t Stat	3,9943	4,4181	5,0737	4,2036	4,8017	3,9763	4,5579	0,5392
P-value	0,0001	0,0000	0,0000	0,0000	0,0000	0,0001	0,0000	0,5900
Lower 95%	0,1069	0,0637	0,1195	0,0647	0,0553	0,0175	0,0520	-0,3287
Upper 95%	0,3137	0,1656	0,2704	0,1780	0,1318	0,0517	0,1308	0,5773
DCP Variable								
Coefficient	0,1700	0,1052	0,0884	0,0623	0,0356	0,0468	0,0813	0,1332
Standard Error	0,0158	0,0130	0,0147	0,0128	0,0146	0,0136	0,0135	0,0300
t Stat	10,7300	8,1030	6,0144	4,8774	2,4487	3,4341	6,0379	4,4432
P-value	0,0000	0,0000	0,0000	0,0000	0,0146	0,0006	0,0000	0,0000
Lower 95%	0,1389	0,0797	0,0595	0,0372	0,0071	0,0201	0,0548	0,0743
Upper 95%	0,2011	0,1307	0,1172	0,0874	0,0642	0,0736	0,1077	0,1921
ANOVA								
SS	231,1325	32,1946	38,6599	14,4182	1,6545	0,6491	10,6316	492,1667
MS	231,1325	32,1946	38,6599	14,4182	1,6545	0,6491	10,6316	492,1667
F	115,1337	65,6589	36,1726	23,7889	5,9962	11,7931	36,4560	19,7418
Significance F	0,0000	0,0000	0,0000	0,0000	0,0146	0,0006	0,0000	0,0000

Figure 5 shows that by taking differences we get stationary data (three variables have p-value less than 5% which means that we reject the presence of unit root).

Figure 5 - Correlogram of ΔACF for ΔFP(a), ΔTP(b) and ΔCP(c)



(a) (b) (c)

This issue is important specially as it strongly impact the reliability of forecasts.

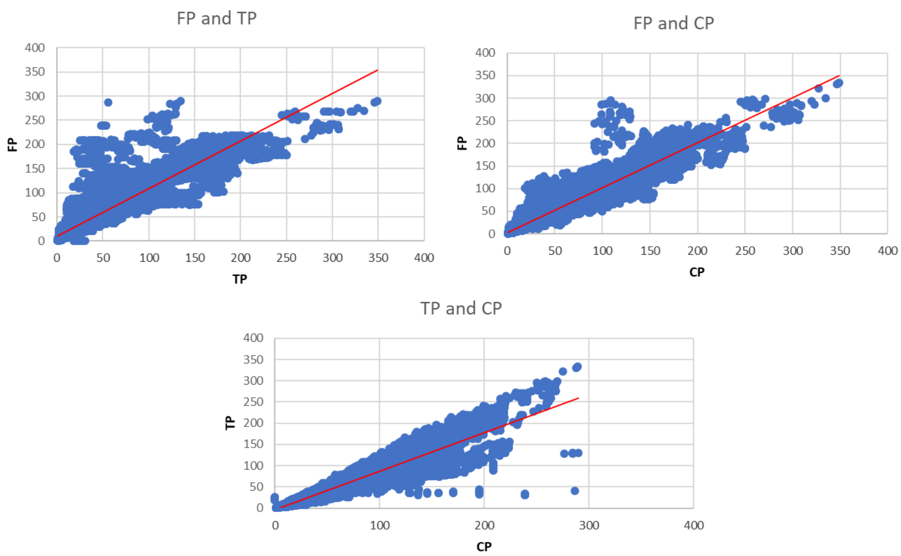
In fact, regression in levels show point to the existence of relationships between variables that do not actually exist (see Figure 6 (a) and Table 9 (a)).

By looking to Figure 6 (a) is the proof that we can be induced in error because our variables seem correlation. But from Figure 6 (b) we can see that this not meaningfull relationship between our variables. Only in scatter plot between ΔTP and ΔCP it is possible to identify relationship between the variables.

From Table 9 (a), we can observe that the panel regressions in levels presents independent variables are highly significant, high R^2 and a highly significant F statistic. If these relations would not be spurious, simple capitalized current prices (CP) would present future prices better than target prices (TP). However, an extremely small Durbin-Watson value (0,019, 0,047 and 0,037), show the relations are indeed spurious and should not be analyzed. According to Granger and Newbold (2001), we should suspect that a regression is spurious if $R^2 > d$, where d is the Durbin-Watson statistic.

Figure 6 - Scatter plot of variables

(a) Levels:



(b) Differences:

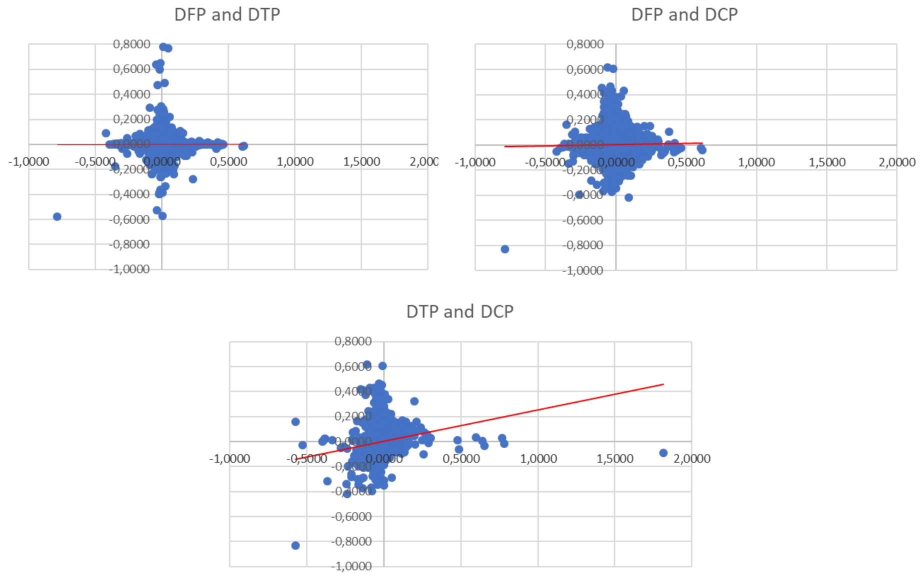


Table 9 - Panel data regressions

(a) Levels:

Dependent Variable: FP
Method: Panel Least Squares
Sample (adjusted): 4/26/2005 4/23/2019
Periods included: 731
Cross-sections included: 50
Total Panel (balanced) observations: 36550

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	-1,424	0,134	-10,590	0,000
TP	0,824	0,002	396,586	0,000
R-squared	0,811	Mean dependent var	38,516	
Adjusted R-square	0,811	S.D. Dependent var	39,241	
S.E. Of regression	17,040	Akaike info criterion	8,509	
Sum square resid	106,123	Schwarz criterion	8,509	
Log Likelihood	-155501,3	Hannan-Quinn criter.	8,509	
F-statistic	157280,5	Durbi-Watson stat	0,019	
Prob (F-statistic)	0,000			

Dependent Variable: FP
Method: Panel Least Squares
Sample (adjusted): 4/26/2005 4/23/2019
Periods included: 731
Cross-sections included: 50
Total Panel (balanced) observations: 36550

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	1,789	0,085	20,922	0,000
CP	0,916	0,001	613,740	0,000
R-squared	0,912	Mean dependent var	38,516	
Adjusted R-squared	0,912	S.D. Dependent var	39,241	
S.E. Of regression	11,670	Akaike info criterion	7,752	
Sum square resid	4977847	Schwarz criterion	7,753	
Log Likelihood	-141666,9	Hannan-Quinn criter.	7,752	
F-statistic	376676,4	Durbi-Watson stat	0,047	
Prob (F-statistic)	0,000			

Dependent Variable: TP
Method: Panel Least Squares
Sample (adjusted): 4/26/2005 4/23/2019
Periods included: 731
Cross-sections included: 50
Total Panel (balanced) observations: 36550

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	8,433	0,096	87,712	0,000
CP	0,999	0,002	594,747	0,000
R-squared	0,906	Mean dependent var	48,456	
Adjusted R-square	0,906	S.D. Dependent var	42,886	
S.E. Of regression	13,124	Akaike info criterion	7,987	
Sum square resid	6295006	Schwarz criterion	7,987	
Log Likelihood	-145957,1	Hannan-Quinn criter.	7,987	
F-statistic	353723,7	Durbi-Watson stat	0,037	
Prob (F-statistic)	0,000			

(b) Differences:

Dependent Variable: DFP
Method: Panel Least Squares
Sample (adjusted): 4/26/2005 4/23/2019
Periods included: 730
Cross-sections included: 50
Total Panel (balanced) observations: 36500

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	0,069	0,010	7,192	0,000
DTP	0,007	0,005	1,215	0,224
R-squared	0,000	Mean dependent var	0,070	
Adjusted R-square	0,000	S.D. Dependent var	1,839	
S.E. Of regression	1,839	Akaike info criterion	4,056	
Sum square resid	123419,8	Schwarz criterion	4,057	
Log Likelihood	-740254,86	Hannan-Quinn criter.	4,056	
F-statistic	1,476	Durbi-Watson stat	2,055	
Prob (F-statistic)	0,224			

Dependent Variable: DFP
Method: Panel Least Squares
Sample (adjusted): 4/26/2005 4/23/2019
Periods included: 730
Cross-sections included: 50
Total Panel (balanced) observations: 36500

Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	0,068	0,010	7,012	0,000
DCP	0,029	0,005	5,851	0,000
R-squared	0,001	Mean dependent var	0,070	
Adjusted R-squared	0,001	S.D. Dependent var	1,839	
S.E. Of regression	1,838	Akaike info criterion	4,055	
Sum square resid	123309,2	Schwarz criterion	4,056	
Log Likelihood	-74008,48	Hannan-Quinn criter.	4,056	
F-statistic	34,241	Durbi-Watson stat	2,055	
Prob (F-statistic)	0,000			

Dependent Variable: DTP
Method: Panel Least Squares
Sample (adjusted): 4/26/2005 4/23/2019
Periods included: 730
Cross-sections included: 50
Total Panel (balanced) observations: 36500

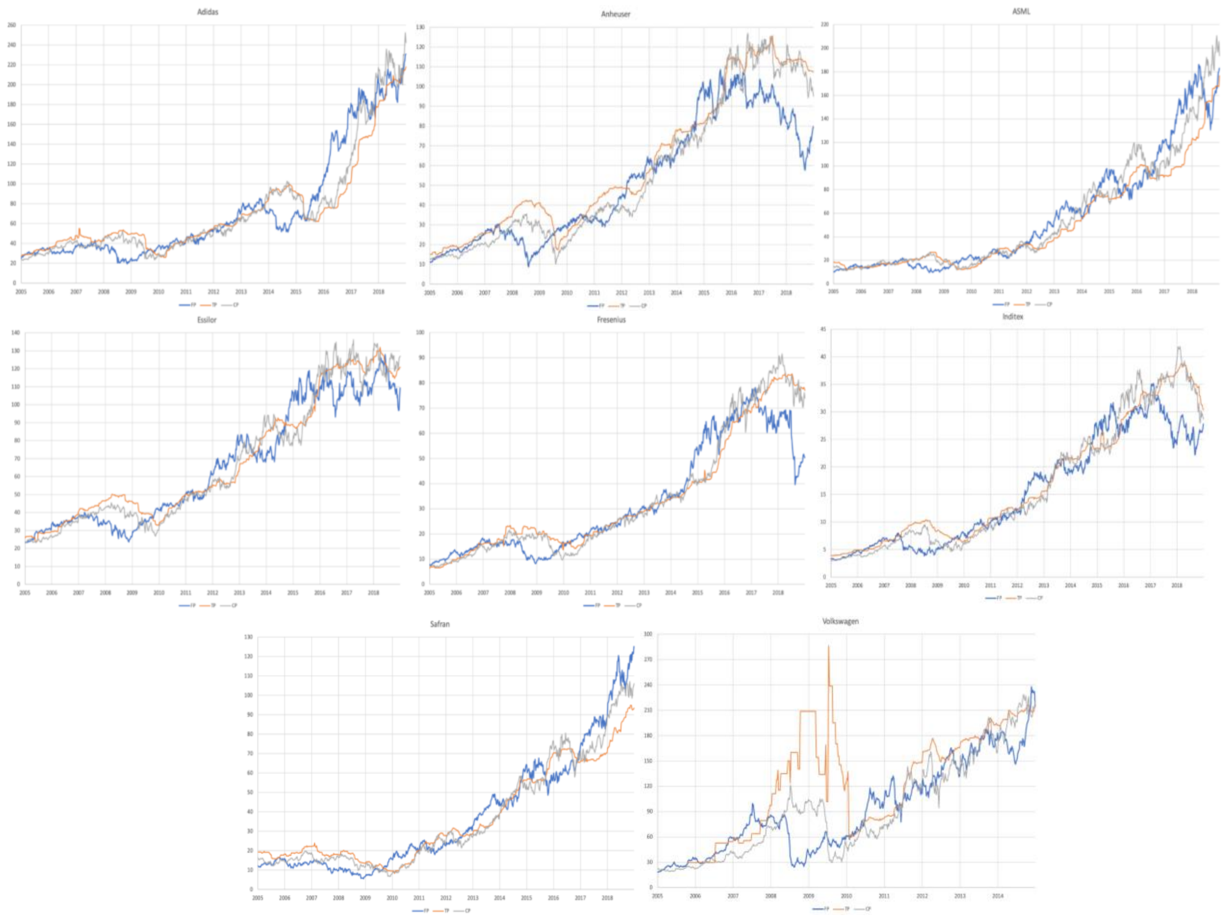
Variable	Coefficient	Std. Error	t-Statistic	Prob.
α	0,051	0,009	5,525	0,000
DCP	0,081	0,004	17,470	0,000
R-squared	0,008	Mean dependent var	0,057	
Adjusted R-square	0,008	S.D. Dependent var	1,758	
S.E. Of regression	1,750	Akaike info criterion	3,958	
Sum square resid	111837,6	Schwarz criterion	3,958	
Log Likelihood	-72226,43	Hannan-Quinn criter.	3,958	
F-statistic	305,203	Durbi-Watson stat	2,007	
Prob (F-statistic)	0,000			

On the other hand, Table 9 (b) show the results from the panel regressions in differences. From the extremely low R^2 and not statistical significance of the explanatory variables in all regressions we can conclude that target prices have no predictive power about future market prices. However, simple CP prices seems to explain FP. Furthermore, from the third regressions we can conclude target prices are correlated with capitalized current prices.

5.2. Results for actively using analysts' recommendations

To understand the behavior of our variables we present graphically their evolution in 8 companies (stocks that compose the tangent portfolio without short selling) and we conclude that TP and CP have a similar performance, see Figure 7. In Figures A.5 to A.7 in the Appendix we present individual regressions for each company.

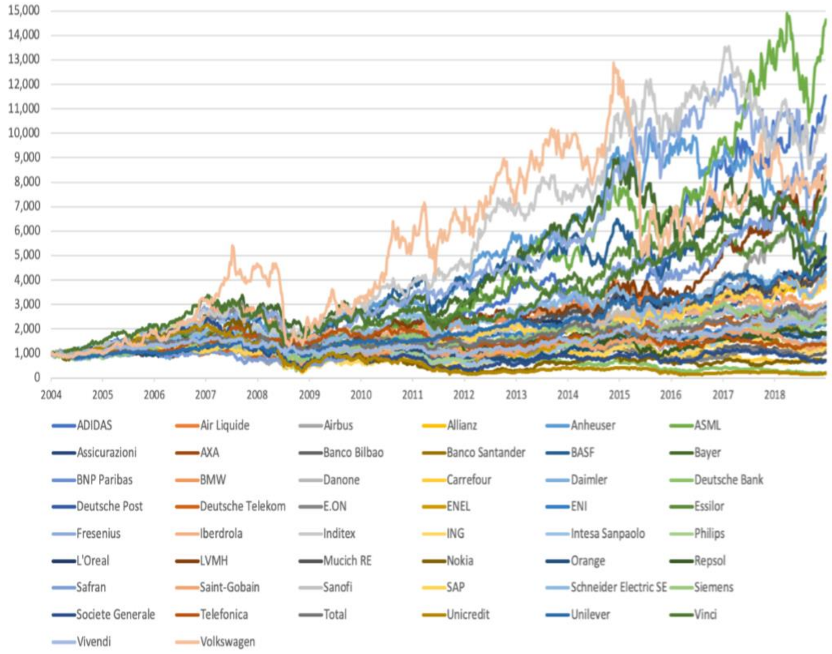
Figure 7 - Evolution of FP, TP and CP



By analyzing the regressions represented in the Appendix we conclude (as we already mentioned) that TP seems a good explanatory variable to FP but does not.

Then, for illustrative effect Figure 8 presents the evolution in each stock, if as we mentioned in Section 4.2.4., we invest 1000€ initial and individually. After 15 years we obtain more than the index.

Figure 8 - Individual stock evolution

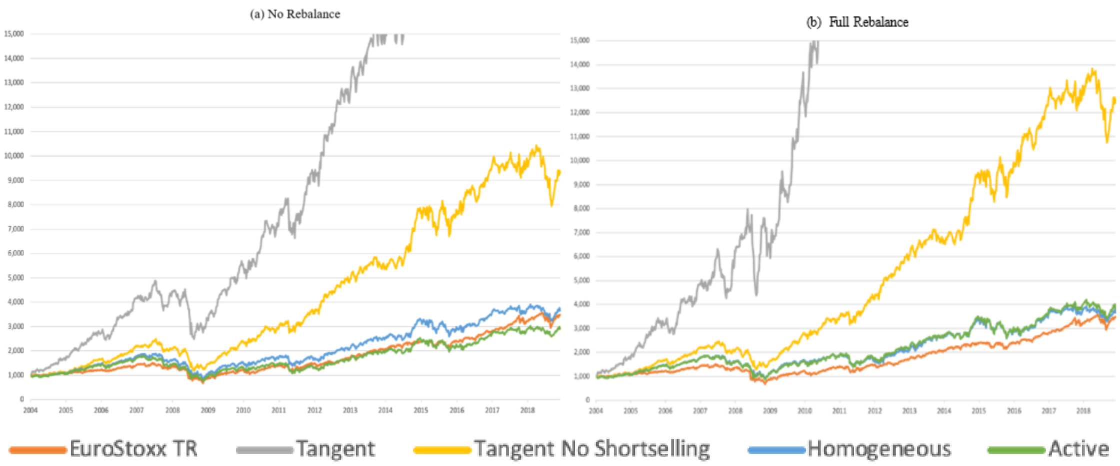


The first step before obtaining portfolio values is to calculate portfolio weights. To help to understand what happens with each portfolio, we represent how each rebalance schemes behaves in Figure A.8 in the Appendix. We conclude that regardless of the rebalancing strategy used, tangent with short selling is the best portfolio (see Figure A.8 (a) in the Appendix). If we look to tangent portfolio without short selling (see Figure A.8 (b) in the Appendix), we obtain higher values than the index but not so good as tangent with short selling. In the case of homogeneous portfolio, the more rebalancing there is, the greater the value of the portfolio (see Figure A.8 (c) in the Appendix). By looking to Figure A.8 (d) in the Appendix we can see that active portfolio behaves better than the homogeneous portfolio just in full rebalance.

As a conclusion, it is observable that when we compare the EURO STOXX 50® Index with the portfolios they all perform better than the index itself, with few exceptions.

To procede we decide to present just extreme of rebalancing schemes: no rebalance and weekly rebalance (full rebalance) and comparing them with the EURO STOXX 50® Index. We can prove that in no rebalance case (see Figure 9 (a)) the active portfolio is the one with the worse behavior comparing with EURO STOXX 50® Index. However, when we decide to rebalance every week (see Figure 9 (b)) we obtain better results in every portfolio.

Figure 9 - Portfolio Evolution



We can see also that the value of the return and risk, in most rebalancing strategies, decrease when we rebalance less. As for the return value it is visible that the best strategy is the full rebalance.

By looking to Table 10 we conclude that each portfolio is preferable in full rebalance terms. But for 61,75% of return we can obtain 33,31% of risk, implying Sharpe Ratio of 1,721. Thus, comparing all values together, we realize that the portfolio with short selling is more efficient than other portfolios.

As a conclusion, if an investor wants to invest in one of these portfolios the best choice is the tangent portfolio with short selling because a higher value of Sharpe Ratio means greater returns relative to the inherent risk, which means a better investment.

We can see in Table 10 that the portfolio that give us higher final return is tangent with short selling, tangent without short selling, active and homogeneous respectively.

If we continue to analyze Table 10, we also see that annual and no rebalancing schemes have the same expected return, risk and Sharpe ratio. This means that no rebalancing or rebalance in annual terms is the same in terms of expected results. However, comparing full rebalance with MVT we obtain similar results.

Table 10 - Resume of portfolio and various rebalancing schemes

Homogeneous

	MVT	Full	Monthly	Semi-annual	Annual	No
Rbar	11,14%	11,14%	10,92%	10,58%	10,90%	10,90%
Vol	20,45%	20,46%	20,39%	20,20%	19,01%	19,01%
SR	0,328	0,328	0,319	0,305	0,341	0,341

TNS

	MVT	Full	Monthly	Semi-annual	Annual	No
Rbar	18,93%	18,93%	18,58%	18,20%	17,00%	17,00%
Vol	17,99%	18,00%	17,97%	17,99%	18,06%	18,06%
SR	0,807	0,806	0,788	0,766	0,697	0,697

Tangent

	MVT	Full	Monthly	Semi-annual	Annual	No
Rbar	61,75%	61,75%	60,19%	56,53%	24,95%	24,95%
Vol	33,31%	33,33%	33,19%	31,11%	20,77%	20,77%
SR	1,721	1,720	1,681	1,675	0,989	0,989

Active

	MVT	Full	Monthly	Semi-annual	Annual	No
Rbar	n.a.	11,86%	11,21%	9,97%	9,60%	9,60%
Vol	n.a.	21,44%	21,32%	21,30%	20,21%	20,21%
SR	n.a.	0,347	0,318	0,261	0,256	0,256

The separation property says that there are two independent tasks involved with the portfolio choice property. The first is determining the optimal risky portfolio and we do it for our portfolios (represented in first column of Table 10).

By formula (15) we get the following results for the EF:

$$\begin{cases} \bar{R}_p = 0{,}04418 + 1{,}7212\sigma_p & for\ \sigma < 0{,}3331 \\ \sigma_p^2 = 0{,}3909\bar{R}_p^2 - 0{,}0956\bar{R}_p + 0{,}0210 & for\ \sigma \geq 0{,}3331 \end{cases}$$

6. Conclusions

In conclusion, in order to answer the first research question, we find that all our variables are not stationary. Thus, the results for level regressions are not meaningful and can be interpreted as spurious. After this, we decide to use differentiated variables to get stationary data and not to be misled in the results. We can conclude, both target prices and simple capitalized current prices have no predictive power about future market prices. Furthermore, we can reinforce target prices are uncorrelated with capitalized current prices. Which means that the predictive power of analyst recommendations does not generate valuable information. That is, the recommendations given by analysts are bad predictors of real future prices. But if we look into differences terms, we also see that DTP does not explain DFP. However, DCP seems to explain DFP and DCP seems to explain DTP. Which in fact make sense because CP are calculated based on average returns and TP is a provision of FP.

For the second question, we conclude that annual and no rebalancing schemes have the same expected return, risk and Sharpe ratio. This means that no rebalancing or rebalance in annual terms is the same in terms of expected results. However, comparing full rebalance with MVT we obtain similar results. This give us the finding that making full rebalance is the best rebalancing scheme. We reach, also, that the homogeneous portfolio has better results than the active (built based on recommendations).

In order to make the study more robust we decide to build tangent portfolios (considering short selling allowed and short selling forbidden) where we conclude that the tangent portfolio with short selling have better behavior comparing to other portfolios and even with the EURO STOXX 50® Index. This result is obtained in full rebalance scheme and gives 61,75%, 33,31% and 1,721 of expected return, risk and Sharpe ratio respectively. As a curiosity we see that if an investor decides to invest in some stock individually obtain higher value than investing in the index.

Despite being an increasingly talked topic, this work has as its main limitations the fact that there are no related studies and in using price targets is that the TP depends on the correct estimate of the final sales price of the product. This means that estimation errors may justify the conclusions we have reached. One of the criticisms of the Markowitz model is precisely the instability of the tangent portfolios generated, in relation to obtaining completely different results related to small variations in the parameters of the variables. This was verified in this study when we decided to consider a larger number of variables in the model.

While this study focusses on target prices and closing prices, it would be important to test more different variables to see if the conclusions are different. Therefore, we could expect different results from those obtained if the parameters of the variables were different: values based on a different time horizon or the use of other assets to make the portfolio.

As future studies, it would be interesting to include other factors (such as include companies' sector) that may explain the behavior of TP in the study of their predictive power and recommendation-based portfolio construction.

Additionally, it is suggested to use different information for the optimization model. In alternative of Markowitz theory use, for example, Scenario approach – Markowitz 2.0 as Kaplan and Savage (2012) did. They suggest the use of the geometric mean return instead of the arithmetic mean return and the use of (C)VaR instead of the standard deviation of returns.

In any case, the Markowitz model has been and continues to be the basis for risk management and efficient portfolio construction. Understanding how your instruments work is critical for anyone who wants to delve deeper into more robust and accurate portfolio selection models.

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Appendices

Table A.1 represents a panel data set in a specific point and is illustrative because we do it for 731 dates for each company.

Table A.1 – Panel data set

Company	*i*	*t*	FP (€)	TP (€)	CP (€)
Adidas	22	26/04/2005	24,80	27,27	24,53
Air Liquide	1	26/04/2005	27,66	37,07	30,09
Airbus	2	26/04/2005	18,08	18,30	20,57
Allianz	3	26/04/2005	52,68	108,23	59,38
Anheuser	4	26/04/2005	11,47	14,96	12,87
ASML	5	26/04/2005	10,40	18,42	15,63
Assicurazioni	6	26/04/2005	14,31	21,52	13,90
AXA	7	26/04/2005	10,27	19,78	10,68
Banco Bilbao	8	26/04/2005	5,90	11,28	5,70
Banco Santander	9	26/04/2005	3,38	9,09	3,62
BASF	10	26/04/2005	15,40	25,11	14,87
Bayer	11	26/04/2005	17,39	22,70	16,41
BMW	13	26/04/2005	22,67	40,37	28,38
BNP Paribas	12	26/04/2005	30,05	54,23	31,71
Carrefour	15	26/04/2005	23,23	38,37	23,68
Daimler	16	26/04/2005	18,88	39,34	26,33
Danone	14	26/04/2005	24,39	32,66	25,73
Deutsche Bank	17	26/04/2005	36,45	57,72	38,91
Deutsche Post	18	26/04/2005	10,98	19,51	12,01
Deutsche Telekom	19	26/04/2005	6,64	17,47	6,93
E.ON	20	26/04/2005	9,92	17,42	8,70
ENEL	21	26/04/2005	2,64	6,17	2,39
ENI	23	26/04/2005	8,51	18,40	7,80
Essilor	24	26/04/2005	23,46	25,73	23,26
Fresenius	25	26/04/2005	7,86	6,32	7,50
Iberdrola	26	26/04/2005	2,51	4,56	2,26
Inditex	27	26/04/2005	3,39	3,92	3,15
ING	28	26/04/2005	11,73	17,28	10,77
Intensa Sanpaolo	29	26/04/2005	1,93	3,05	1,57
L'Oreal	31	26/04/2005	43,54	69,50	55,84
LVMH	32	26/04/2005	37,61	61,88	48,20
Munich RE	33	26/04/2005	46,51	105,79	56,30
Nokia	34	26/04/2005	7,50	14,03	7,71
Orange	35	26/04/2005	9,04	28,19	8,60
Philips	30	26/04/2005	12,73	28,14	17,34
Repsol	45	26/04/2005	9,31	16,98	9,00
Safran	36	26/04/2005	12,20	19,40	16,64
Saint-Gobain	37	26/04/2005	26,05	41,88	24,79
Sanofi	38	26/04/2005	40,57	60,00	32,47
SAP	39	26/04/2005	24,85	35,10	30,25
Schneider Electric SE	40	26/04/2005	17,87	30,19	20,33
Siemens	41	26/04/2005	36,91	70,60	44,79
Societe Generale	42	26/04/2005	44,87	70,88	43,42
Telefonica	43	26/04/2005	5,87	14,58	5,78
Total	44	26/04/2005	21,37	40,65	20,15
Unicredit	46	26/04/2005	83,10	128,61	72,10
Unilever	47	26/04/2005	10,16	21,74	12,78
Vinci	48	26/04/2005	16,31	19,78	13,37
Vivendi	49	26/04/2005	10,13	23,51	10,30
Volkswagen	50	26/04/2005	18,55	0,00	22,95

Table A.2. present the active portfolio composition evolution in annual terms.

Table A.2 – Active portfolio composition evolution (annual)

	Inicial	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	final
Adidas	1,03%	1,19%	1,51%	0,68%	1,39%	0,78%	0,88%	1,61%	2,06%	2,51%	3,66%	0,29%	-0,15%	-0,78%	3,69%	4,13%
Air Liquide	1,48%	1,68%	1,50%	1,68%	1,74%	2,85%	2,27%	2,26%	2,80%	2,85%	2,29%	3,11%	2,34%	-0,09%	1,56%	1,74%
Airbus	0,17%	1,00%	1,15%	0,29%	0,47%	0,33%	0,56%	0,56%	1,18%	1,60%	2,74%	2,16%	3,45%	1,59%	2,53%	3,19%
Allianz	8,11%	7,58%	8,76%	9,55%	7,45%	7,06%	6,77%	6,27%	6,39%	6,24%	7,23%	6,84%	7,80%	7,10%	5,49%	6,17%
Anheuser	0,58%	0,93%	0,92%	0,94%	1,49%	1,32%	2,00%	2,10%	1,89%	3,39%	2,43%	3,98%	3,58%	6,60%	5,99%	5,75%
ASML	0,84%	0,47%	0,22%	0,30%	0,25%	0,15%	0,71%	1,07%	0,70%	0,48%	2,69%	0,55%	1,98%	0,75%	4,16%	4,70%
Assicurazioni	1,19%	1,20%	1,41%	1,15%	1,04%	0,74%	0,97%	0,77%	0,83%	0,49%	0,65%	1,11%	0,96%	0,87%	0,13%	0,13%
AXA	1,49%	1,57%	1,83%	1,88%	1,44%	1,28%	1,56%	1,21%	1,32%	1,17%	1,17%	1,52%	1,45%	1,57%	1,04%	1,09%
Banco Bilbao	0,84%	0,90%	0,91%	1,16%	0,88%	0,63%	0,96%	0,62%	0,51%	0,47%	0,38%	0,41%	0,25%	-0,14%	0,29%	0,25%
Banco Santander	0,82%	0,78%	0,84%	0,98%	0,84%	0,67%	1,11%	0,74%	0,56%	0,37%	0,17%	0,22%	0,17%	-0,06%	0,23%	0,20%
BASF	1,77%	2,01%	1,59%	1,64%	1,75%	1,39%	2,41%	2,86%	3,11%	3,38%	2,85%	1,33%	1,32%	2,98%	3,80%	3,33%
Bayer	1,20%	1,16%	1,39%	1,58%	1,86%	3,11%	2,37%	2,24%	2,58%	2,38%	2,75%	4,94%	4,56%	4,44%	5,28%	3,42%
BNP Paribas	3,66%	3,75%	4,15%	4,28%	3,14%	2,03%	4,80%	4,28%	3,46%	3,89%	3,43%	2,50%	2,97%	2,25%	2,75%	2,14%
BMW	2,18%	2,03%	1,80%	1,81%	1,68%	0,98%	1,55%	2,95%	4,33%	4,28%	4,20%	5,64%	4,41%	4,36%	2,27%	1,97%
Danone	1,32%	1,47%	1,52%	2,05%	1,78%	2,48%	2,12%	1,64%	1,74%	1,67%	1,32%	1,12%	2,29%	3,96%	2,45%	2,67%
Carrefour	2,14%	1,75%	1,45%	1,34%	1,67%	1,26%	1,35%	1,51%	0,95%	0,77%	0,59%	1,18%	1,05%	2,23%	0,76%	0,77%
Daimler	2,29%	1,92%	2,59%	2,54%	3,34%	1,25%	2,14%	3,62%	3,47%	2,60%	3,26%	4,68%	5,41%	4,37%	2,82%	2,51%
Deutsche Bank	2,56%	2,85%	2,14%	2,82%	1,54%	-0,11%	2,00%	1,72%	1,18%	1,25%	1,49%	0,86%	0,63%	-0,53%	0,09%	0,05%
Deutsche Post	1,25%	1,53%	1,32%	1,14%	1,16%	0,81%	0,94%	1,00%	0,79%	0,95%	1,09%	1,07%	0,73%	1,55%	1,02%	0,85%
Deutsche Telekom	1,58%	1,46%	1,08%	0,74%	0,76%	1,07%	0,71%	0,65%	0,59%	0,47%	0,45%	0,46%	0,82%	1,37%	0,82%	0,94%
E.ON	1,31%	1,53%	1,90%	1,83%	2,11%	1,90%	1,72%	1,13%	0,95%	0,53%	0,32%	0,49%	0,31%	0,30%	0,48%	0,54%
ENEL	0,57%	0,49%	0,43%	0,49%	0,39%	0,39%	0,33%	0,26%	0,21%	0,14%	0,12%	0,23%	0,23%	0,33%	0,19%	0,21%
ENI	1,60%	1,74%	1,82%	1,59%	1,40%	2,14%	1,54%	1,34%	1,42%	1,41%	0,87%	0,63%	0,63%	1,53%	0,28%	0,28%
Essilor	0,76%	0,76%	0,78%	0,92%	1,06%	0,95%	1,43%	0,67%	0,57%	1,01%	2,75%	2,25%	2,94%	3,61%	2,01%	1,92%
Fresenius	0,00%	0,24%	0,40%	0,61%	0,37%	1,29%	0,53%	0,45%	0,94%	0,81%	1,08%	0,63%	1,15%	3,94%	3,19%	2,49%
Iberdrola	0,37%	0,35%	0,37%	0,38%	0,55%	0,76%	0,54%	0,40%	0,41%	0,27%	0,16%	0,26%	0,27%	0,41%	0,27%	0,34%
Inditex	0,19%	0,20%	0,21%	0,26%	0,29%	0,29%	0,46%	0,34%	0,58%	0,74%	0,74%	0,44%	1,34%	1,80%	1,45%	1,65%
ING	1,11%	1,02%	0,98%	1,01%	0,74%	0,38%	0,42%	0,41%	0,59%	0,53%	0,57%	0,62%	0,85%	0,60%	0,70%	0,59%
Intesa Sanpaolo	0,23%	0,24%	0,30%	0,29%	0,22%	0,13%	0,24%	0,16%	0,14%	0,08%	0,12%	0,17%	0,26%	0,13%	0,10%	0,08%
Philips	1,76%	1,25%	1,47%	1,26%	1,22%	0,53%	1,37%	1,54%	0,81%	1,46%	1,26%	0,84%	0,89%	0,58%	0,36%	0,37%
L'Oreal	2,90%	2,24%	2,04%	2,09%	2,30%	1,83%	2,08%	2,77%	1,87%	0,33%	2,94%	2,29%	2,69%	0,52%	0,88%	1,11%
LVMH	3,07%	2,42%	2,86%	2,77%	2,39%	1,97%	3,87%	4,08%	5,38%	6,57%	4,39%	5,82%	6,31%	3,09%	2,22%	2,72%
Mucich RE	8,01%	7,35%	6,98%	6,94%	6,35%	9,61%	7,88%	6,30%	6,34%	5,83%	4,72%	5,27%	7,24%	4,19%	2,81%	3,23%
Nokia	0,95%	1,82%	0,73%	0,89%	1,07%	0,92%	0,72%	0,36%	0,17%	0,11%	0,25%	0,37%	0,55%	0,33%	0,12%	0,12%
Orange	2,88%	2,23%	1,65%	1,32%	1,43%	2,42%	1,65%	1,18%	0,95%	0,65%	0,24%	1,02%	0,98%	1,81%	0,73%	0,73%
Repsol	1,24%	1,44%	1,50%	1,33%	1,27%	1,66%	1,65%	1,81%	1,76%	1,36%	1,25%	0,87%	0,41%	0,72%	0,40%	0,40%
Safran	0,81%	0,79%	0,72%	0,40%	0,35%	0,45%	0,75%	0,95%	0,93%	1,25%	2,38%	1,56%	1,37%	-1,54%	1,01%	1,39%
Saint-Gobain	2,44%	2,70%	2,20%	2,85%	2,38%	1,76%	2,03%	2,06%	2,60%	1,63%	1,43%	1,81%	1,22%	0,86%	2,34%	1,96%
Sanofi	4,30%	5,52%	4,42%	3,11%	2,65%	3,84%	3,76%	2,64%	2,70%	3,49%	3,47%	3,82%	3,67%	3,17%	3,92%	4,57%
SAP	1,18%	1,44%	1,37%	1,19%	0,82%	0,82%	1,11%	1,24%	1,69%	2,19%	2,25%	1,36%	2,35%	2,08%	3,63%	4,08%
Schneider Electric SE	1,78%	1,90%	2,04%	2,28%	1,77%	1,28%	2,04%	2,94%	2,41%	2,18%	2,07%	3,28%	1,38%	0,53%	1,64%	1,66%
Siemens	4,34%	3,84%	3,31%	3,53%	3,52%	2,69%	3,62%	4,95%	4,44%	4,26%	4,91%	3,62%	3,15%	4,44%	6,54%	6,62%
Societe Generale	4,36%	3,96%	4,40%	4,24%	2,44%	1,96%	3,16%	3,39%	2,03%	2,43%	2,43%	2,30%	2,36%	1,70%	1,65%	1,06%
Telefonica	1,30%	1,11%	1,02%	1,01%	1,31%	1,86%	1,56%	1,28%	1,05%	0,65%	0,47%	0,54%	0,73%	0,42%	0,48%	0,44%
Total	3,19%	3,68%	4,05%	3,33%	3,09%	4,87%	3,75%	3,23%	3,18%	3,46%	2,04%	2,31%	1,73%	4,50%	1,15%	1,17%
Unicredit	8,12%	6,24%	6,51%	6,59%	5,50%	-0,60%	4,16%	2,57%	1,48%	0,46%	0,73%	0,79%	1,50%	0,32%	0,67%	0,45%
Unilever	1,49%	0,89%	0,94%	0,72%	0,88%	1,31%	1,02%	1,00%	1,00%	1,30%	0,87%	1,02%	1,43%	2,32%	1,50%	1,74%
Vinci	1,22%	1,93%	2,36%	2,20%	3,13%	3,20%	3,42%	3,06%	3,45%	2,48%	1,97%	1,96%	2,57%	2,59%	3,22%	3,44%
Vivendi	2,02%	2,03%	1,92%	1,96%	1,92%	2,47%	1,62%	1,56%	1,24%	1,14%	1,30%	1,04%	0,96%	0,91%	0,65%	0,80%
Volkswagen	0,00%	1,45%	2,22%	4,03%	11,42%	16,84%	3,37%	6,25%	8,27%	10,05%	7,04%	8,42%	2,50%	9,44%	8,27%	7,82%

Figure A.1 – Homogeneous portfolio: weights

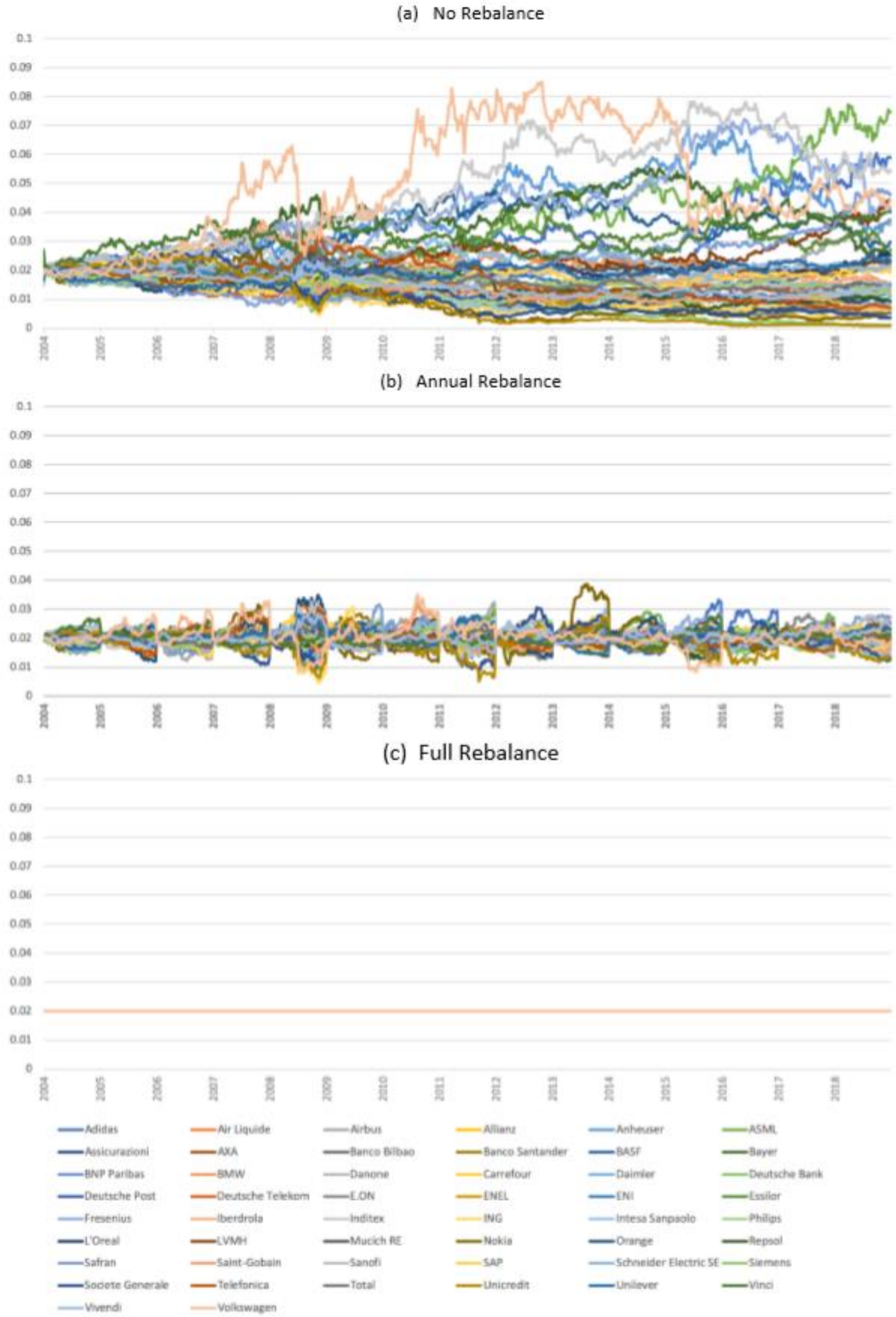

Figure A.2 – Tangent portfolio: weights

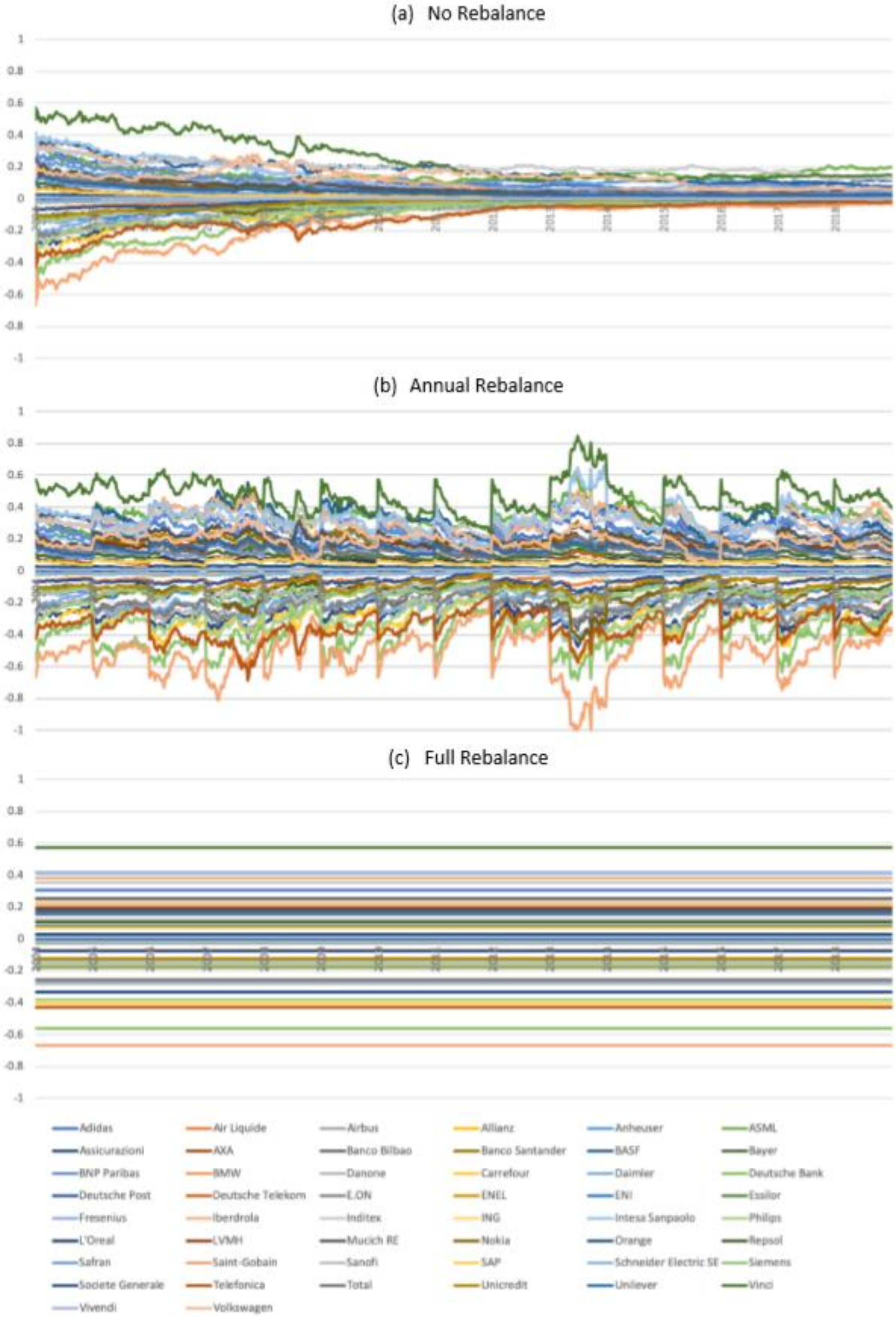

Figure A.3 – Tangent without short selling: weights

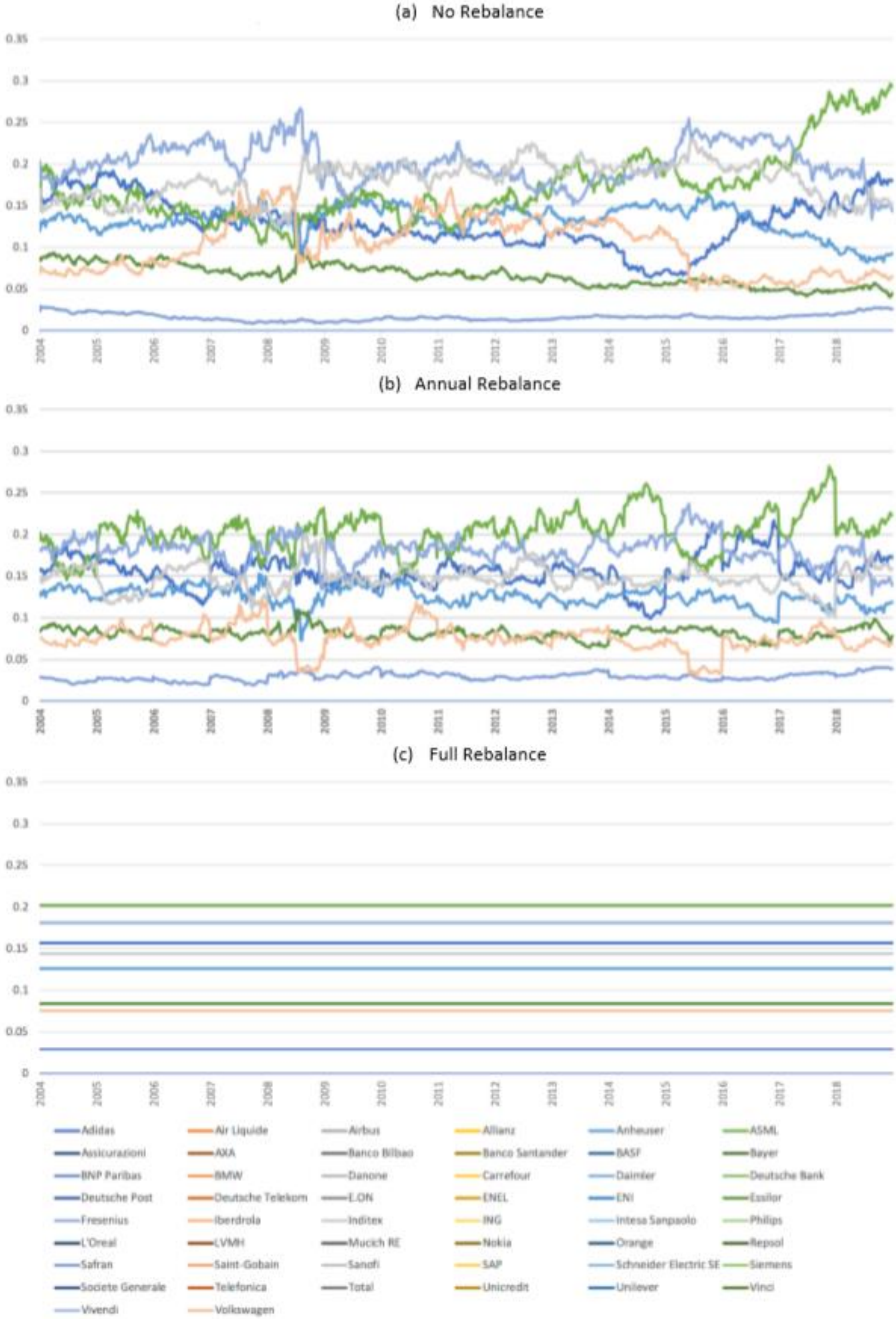

Figure A.4 – Active portfolio: weights

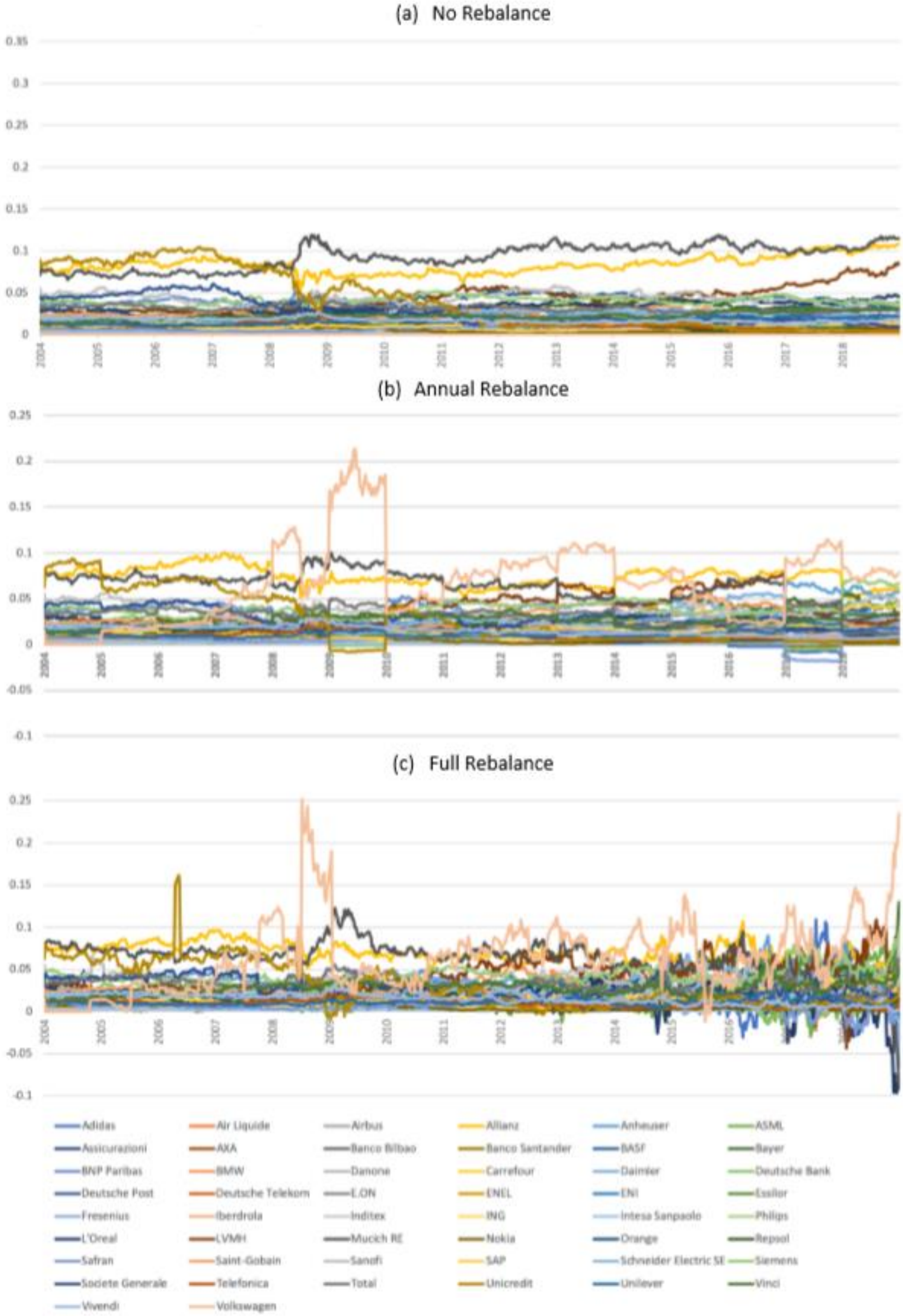

Figure A.5 – Adidas, Anheuser and ASML regressions in Levels (a) and in Differences (b)

(a) (b) (a) (b) (a) (b)

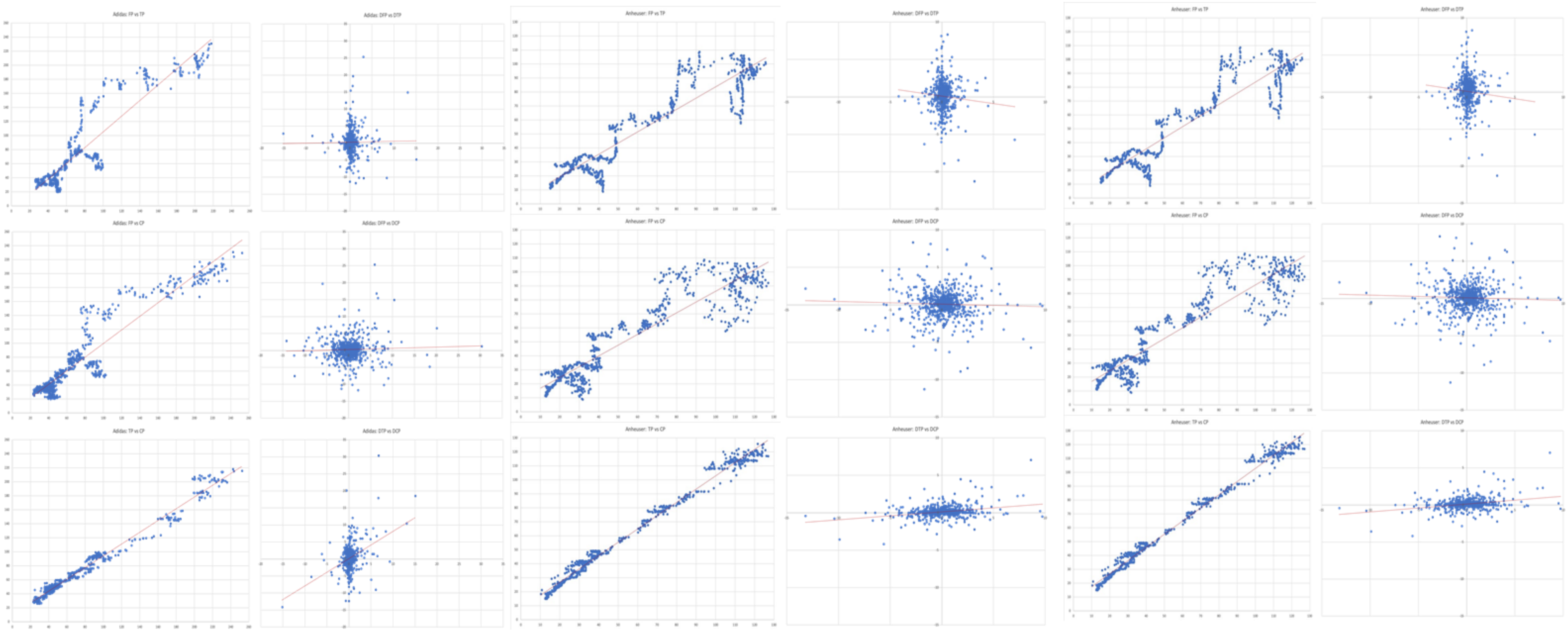

Figure A.6 – Essilor, Fresenius and Inditex regressions in Levels (a) and in Differences (b)

(a) (b) (a) (b) (a) (b)

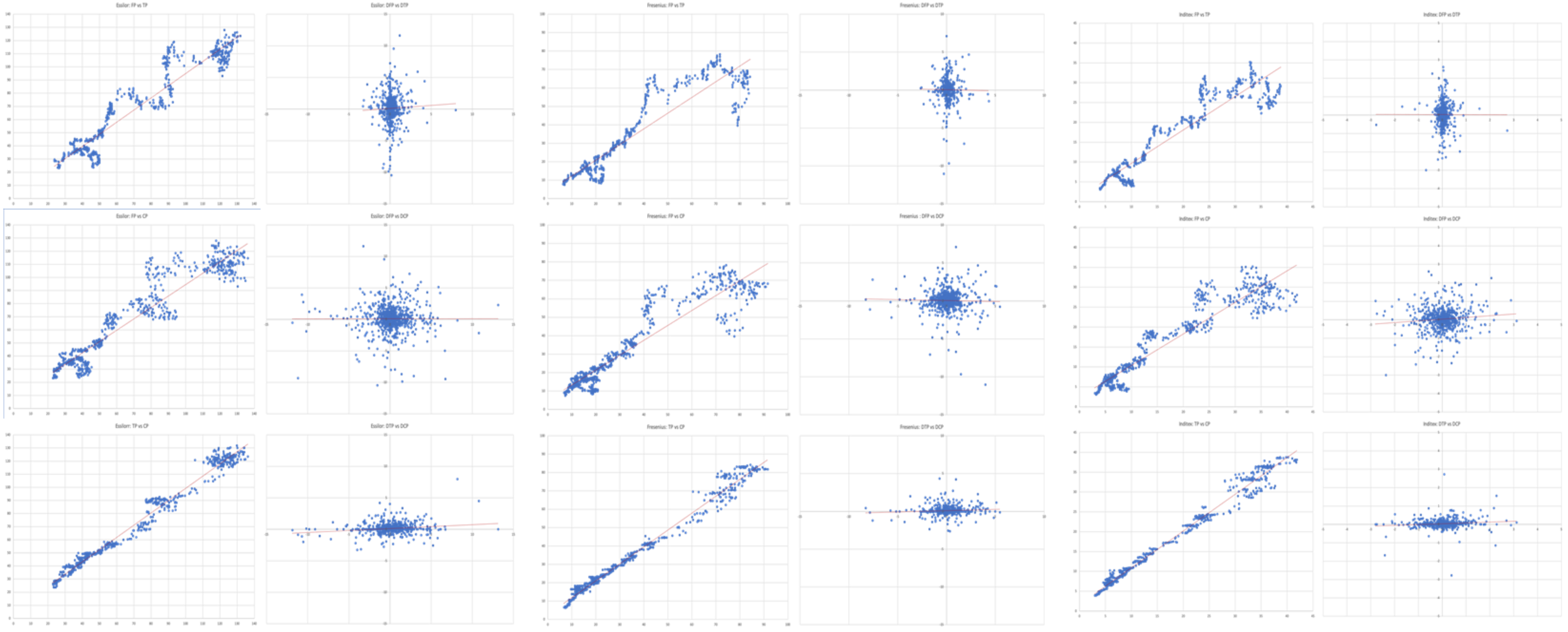

Figure A.7 - Safran and Volkswagen regressions in Levels (a) and in Differences (b)

(a) (b) (a) (b)

Figure A.8 – Evolution for different rebalancing schemes